Comparative Analysis of Innovation Districts to Set Up Performance Goals for Tec Innovation District

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ABSTRACT

Purpose: Innovation districts represent a way to create, foster, and manage innovation. Different regions apply their strategy according to the dominant stakeholder in the region, such as academia, industry, government, or entrepreneurs. This research aims to evaluate different innovation districts from a production system point of view to determine the output goals for a Tec Innovation District.

Methodology/Approach: Data Envelopment Analysis (DEA) was determined to be the best tool for this study; the variable returns to scale output-oriented model was used to determine the goals for the new district; also, the bootstrap method was employed to analyse the efficiency sensitivity in the sample of districts.

Findings: The average technical efficiency of the analysed innovation districts was 0.659, with the highest technical efficiency observed in the case of the Entrepreneurial type (0.831) and Industry Cluster (0.820) districts, whereas the Local government type registered the lowest technical efficiency (0.468).

Research Limitation/Implication: The projections for the Tec Innovation District's output variables were obtained using a set of U.S. innovation districts due to the similarity of the studied region to the available group. The research allowed us to determine realistic outputs for the studied innovation district.

Originality/Value of paper: The study employs an original DEA for comparing innovation districts and performs a bootstrap to study the system's robustness; within this research, the performance level of a new district was calculated to be within a specific efficiency level, according to their peers.

Category: Research paper

Keywords: bootstrap; data envelopment analysis; efficiency goals; innovation districts

1 INTRODUCTION

Innovation has been determined to be essential for the prosperity of regional economies (Hoffecker and Rubenstein, 2019). But how can it be triggered? In the last few decades, it has been found that the innovation process can be managed, promoted, and triggered (Ángel Álvarez, 2009). The government, universities, and industrial sectors have been looking for the best way to trigger innovation and tackle the problems within their region (Etzkowitz and Leydesdorff, 2000). Innovation Districts represent one way of creating and managing innovation; these are defined as "a specific geographic location, generally within a city, where high concentrations of people work in knowledge-intensive industries in conjunction with other related companies and institutions" (Burke and Gras, 2019). Innovation District's idea goes beyond just a place for companies to work. Innovation Districts also offer a great place to live. Within such a place, there may be pleasant housing opportunities, safe public spaces, and leisure activities (Adu-McVie et al., 2021). That is why Innovation Districts are a viable economic growth model, as their goal is to be economically, spatially, and socially attractive to people with an elevated level of knowledge capable of discussing and creating solutions that tackle regional, national, or global challenges (Esmaeilpoorarabi et al., 2020). In other words, Innovation Districts pretend to be a problem-solving society that brings prosperity to their region and the world.

According to the Global Institute of Innovation Districts (GIID) (2022), there are over one hundred Innovation Districts around the globe. GIID has been researching Innovation Districts to identify what makes a district an economic engine to its region. GIID works with twenty-three districts across different regions, such as Europe, North America, The Middle East, Australia, and Asia. In the case of Latin America, GIID has been collaborating with Innovation Districts in Mexico and Colombia, for example. In the article "New empirical evidence: how one Innovation District is advancing the regional economy," the GIID mentioned the economic impact of The Cortex Innovation Community in St. Louis in the United States, where the district generated around $2 billion in annual regional output (Tripp, 2002), exposing the benefits of innovation-based economic development.

Mexico's economy is mainly based on manufacturing activities. According to Data México (2022), the manufacturing sector registered the highest Gross Domestic Product (GDP), around $280 billion. Fernández and Alva (2018) mentioned that the country needs to move from a manufacturing economy to a knowledge-oriented economy. In this line, Christensen, Ojomo, and Dillion (2019) defined the concept of efficiency innovation as those initiatives that enable a company to do more with fewer resources. The concept is more focused on process innovation rather than on the product itself. The authors mentioned that outsourcing is one of the most popular examples of efficiency innovation. Outsourcing is prevalent among American firms as they commonly outsource part of their manufacturing processes to Mexican plants intending to reduce costs. This happens because a Mexican worker makes around a sixth of what an

American worker makes (Christensen, Ojomo and Dillion, 2019). However, the benefits of those savings go mainly to the foreign companies established in a developed consumption economy. Therefore, it is worthwhile to consider economic models, such as an Innovation District, to enable Mexican companies to integrate market-creating innovation focused on solving problems of a large part of the population (Christensen, Ojomo and Dillion, 2019).

In Mexico’s case, some Innovation Districts are in their early stages. One is in Guadalajara, also known as “The Silicon Valley of Mexico”, with an important role in developing information technology and software (Hoffecker and Rubenstein, 2019). In Mexico City, a project called “Distrito de Innovación Tlapan” (DIT) is still developing to build an Innovation District in the Tlalpan municipality; Universidad Autonoma Metropolitana, Universidad Iberoamericana, Tecnologico de Monterrey campus in Mexico City, and Tlalpan municipality are carrying out this project. The main objective of DIT is to tackle water-related problems and improve mobility in Mexico City’s south region (Medina, 2020). Similarly, another Innovation District called Distrito Tec is currently being developed, in Monterrey, Nuevo León, in the home city of Tecnologico de Monterrey (TEC). TEC is the regional leader in education, innovation, patents, and research, recently ranked as the best university in Mexico and #4 in Latin America (QS Top Universities, 2022). Distrito Tec aims to generate an innovation ecosystem for researchers, entrepreneurs, students, and the academy’s community by developing urban architecture design and infrastructure planning (Solís, 2021).

1.1 Performance Evaluation

Since an Innovation District is a production system that brings wealth to a region (Hoffecker and Rubenstein, 2019), it is worth analysing its performance. In this case, the performance of an Innovation District is understood as a capability to transform their resources in research outcomes with an economic added value in a region. Many quantitative and statistical methods can be applied to evaluate efficiency and performance. Considering the benchmarking techniques, the frontier analysis has become the most noteworthy approach, with Data Envelopment Analysis (DEA) – a non-parametric modelling technique most often used for evaluating the efficiency and performance of the set of decision-making units (Emrouznejad and Yang, 2018) – being its best representative.

DEA has a comprehensive record of successful applications in many industries. For example, Halásková, Mikušová Meričková and Halásková (2022) used DEA to evaluate the efficiency of the services of secondary education in Slovakia. Dénes et al. (2017) applied DEA to measure the efficiency of rehabilitation departments in Hungary. Flegl and Hernández Gress (2023) constructed a DEA model to ass the technical efficiency of public security in Mexico. Avilés-Sacoto et al. (2021) used the DEA methodology to study the environmental performance of 32 states in Mexico. Hosseinzadeh et al. (2023) applied DEA to evaluate the impact of the preselected assets in different portfolio optimization strategies.

DEA has also been used to evaluate innovation performance. For example, for a cross-country comparison, Guan and Chen (2012) constructed a network DEA model to measure the innovation efficiency of the national innovation systems of 22 OECD countries, whereas Aytekin et al. (2022) examined the global innovation efficiency of European Union member countries and candidate countries. Lu, Kweh, and Huang (2014) used the network DEA to evaluate the research and development (R&D) and economic efficiency of the national innovation systems in 30 countries.

Considering regional analyses, Rudskaya et al. (2022) developed a two-stage DEA to assess the effectiveness of regional innovation systems in Russia. Similarly, Broekel, Rogge, and Brenner (2017) investigated the innovation efficiency of 150 German labor market regions through a shared-input DEA model. Dzemydaitė, Dzemyda, and Galinienė (2016) evaluated the efficiency of 40 Eastern and Central European Union regional innovation systems. Kaihua and Mingting (2014) applied DEA to assess the efficiency performance of 30 Chinese regional innovation systems, and Wei (2019) used a three-stage DEA model to measure the regional innovation efficiency of 30 Chinese provinces.

In the Mexican context, Valdez Lafarga and León Balderrama (2015) measured the relative technical efficiency of regional innovation systems in 32 Mexican states. Avilés-Sacoto et al. (2020) used a two-stage DEA analysis to model the efficiency of the regional innovation system in Monterrey.

An overview of the literature review on DEA-based innovation performance evaluation is summarized by Narayanan, Ismail and Mustafa (2022).

1.2 Objective

The objective of the analysis is to evaluate the technical efficiency of the Top 25 Innovation Districts in the United States using the DEA method. To obtain a more robust result, the Bootstrap DEA model is applied. Therefore, the analysis aims to answer the following research questions (RQ):

RQ1: What is the technical efficiency of the Top 25 Innovation Districts?

RQ2: Can differences regarding the Innovation Districts type be observed?

RQ3: Does the Bootstrap methodology detect significant corrections in the technical efficiency?

A secondary objective of the analysis is to use the constructed Bootstrap DEA model to set up performance goals for the Distrito Tec Innovation District. In this case, the following research question is considered:

RQ4: What are the performance goals for Distrito Tec?

2 MATERIALS AND METHODS

DEA allows to evaluate the technical efficiency of homogeneous decision-making units (DMUs) with respect to their capacity to convert m inputs to produce s outputs with input and output values x_{ij} $(i = 1,2,\dots,n, j = 1,2,\dots m)$ and y_{ik} $(i = 1,2,\dots,n, k = 1,2,\dots s)$. The efficiency of the DMU_0 is calculated as the weighted sum of outputs divided by the weighted sum of inputs (Charnes, Cooper and Rhodes, 1978). The linearized envelopment form of the variable returns to scale output-oriented model for the DMU_0 is defined as follows (Toloo, Keshavarz and Hatami-Marbini, 2021):

$$\max \varphi + \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \tag{1}$$

subjected to

$$\begin{aligned} &\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = x_{i0}, \qquad i = 1,2,\dots,m; \\ &\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = \varphi y_{r0}, \qquad r = 1,2,\dots,s; \\ &\sum_{j=1}^{n} \lambda_j = 1; \\ &\lambda_j \geq 0, \qquad j = 1,2,\dots,n. \end{aligned} \tag{2}$$

where x_{ij} is the quantity of the input i of the DMU_j, y_{rj} is the quantity of the output r of the DMU_j, $\lambda_j \geq 0$ is an intensity variable of DMU_j, s_i^- and s_i^+ are the slack variables. DMU_0 is efficient if and only if $\varphi = 1$ and $s_i^- = s_r^+ = 0$ for all i and r, i.e., there is no other DMU that produces more outputs with the same combination of inputs.

2.1 Bootstrap-DEA Method

Bootstrap is a procedure of drawing with replacement from a sample, mimicking the data-generating process of the underlying true model and producing multiple estimates which can be used for statistical inference (Tziogkidis, 2012). The Bootstrap-DEA (B-DEA) was introduced by Simar and Wilson (1998). This method allows to analyse the sensitivity of efficiency scores which results from the distribution of (in)efficiency in the sample. The specific steps of the B-DEA are as follows (Pan, Hong and Kong, 2020):

- Use the traditional DEA method to calculate the initial efficiency scores $\hat{\varphi}_i (i = 1,\dots,n)$ for each DMU.

- Based on $\hat{\varphi}_i(i = 1, \dots, n)$, adopting the Bootstrap method to generate n random efficiency scores $\varphi_{1b}^*, \varphi_{2b}^*, \dots, \varphi_{nb}^*$, where b is the number of iterations.
- Computing the simulation sample (x_{ib}^*, y_{ib}^*), in which $x_{ib}^* = \left(\frac{\hat{\varphi}_i}{\varphi_{ib}}\right) x_i, i = 1,2, \dots, n$.
- Using the DEA model to compute the modified efficiency value $\hat{\varphi}_{bi}$ for each simulation sample.
- Repeating steps ii to iv for B times to obtain a group of efficiency scores $\hat{\varphi}_{bi}, b = 1,2, \dots, B$.
- By simulating the distribution of the original sample estimator, the modified efficiency scores deviation under the Bootstrap-DEA method can be estimated as follows:

$$\text{Bias}(\hat{\varphi}_i) = E(\hat{\varphi}_i) - \hat{\varphi}_i \tag{3}$$

$$\text{Bias}(\hat{\varphi}_i) = B^{-1} \sum_{b=1}^{B} (\hat{\varphi}_{bi}) - \hat{\varphi}_i \tag{4}$$

- The modified efficiency value of the Bootstrap-DEA method can be computed as follows:

$$\tilde{\varphi} = \hat{\varphi}_i - \widehat{\text{Bias}}(\hat{\varphi}_i) = 2\hat{\varphi}_i - B^{-1} \sum_{b=1}^{B\varphi} (\hat{\varphi}_{bi}) \tag{5}$$

In this analysis, the B value was set to 2,000 to secure the accuracy of the sampling (Hall, 1986). The BCC output-oriented envelopment smoothed B-DEA model was used for the calculations. MaxDEA Ultra 7 software was used for all calculations.

2.2 Dataset and Model

Aretian is a team of Harvard affiliates from various schools offering consultancy to address challenges in building thriving urban ecosystems. These are the authors of The Atlas of Innovation Districts (The Atlas), a developed methodology to classify the Top 25 Innovation Districts in the United States based on their performance outputs (Burke and Gras, 2019). The Atlas uses three Key Performance Indicators (KPIs):

- Innovation intensity: It measures the collective effort deployed to create knowledge networks. It is calculated as a percentage of employees working on knowledge-intensive activities per geographic unit.

- Innovation performance: It measures the tangible outputs created annually by the innovation community.

- Innovation impact: It describes the benefits to the broader community that result from the development of knowledge-intensive activities.

The KPIs contain metrics that provide general information about the Innovation Districts, like the number of residents per unit area, number of employees per unit area, number of companies operating in the Innovation District, and its spatial area, among others. The selection of the variables depends on the objective of each study. In general, the variables reflect personnel/employees, such as full-time scientists and engineers (Avilés-Sacoto et al., 2020; Broekel, Rogge, and Brenner, 2017; Kaihua and Mingting, 2014; Lu, Kweh and Huang, 2014; Wei, 2019); R&D expenditures/investments in innovation activities (Avilés-Sacoto et al., 2020; Guan and Chen, 2012; Rudskaya et al., 2022; Wei, 2019); the number of involved organizations/companies (Aytekin et al., 2022; Rudskaya et al., 2022) or number of research centers (Valdez Lafarga and León Balderrama, 2015).

For the outcomes of the innovation process, scientific production, such as published scientific papers (Guan and Chen, 2012; Lu, Kweh and Huang, 2014; Valdez Lafarga and León Balderrama, 2015); number of registered patents (Broekel, Rogge and Brenner, 2017; Kaihua and Mingting, 2014; Lu, Kweh and Huang, 2014; Rudskaya et al., 2022; Valdez Lafarga and León Balderrama, 2015) or generated R&D projects (Avilés-Sacoto et al., 2020); economic indicators, such as added-value of industries (Guan and Chen, 2012) and export of created products (Guan and Chen, 2012); or sales revenues from R&D projects (Avilés-Sacoto et al., 2020; Kaihua and Mingting, 2014).

Therefore, to analyse the performance of the top 25 innovation districts, as well as to determine the performance goals for the Tec Innovation District (TID), the following variables were selected:

- The number of companies (I1): Number of companies established in an Innovation District.
- Employees in innovation (I2): Number of employees working on knowledge creation in each Innovation District.
- (%) Innovative employment (I3): Number of employees whose work is related to knowledge creation, considering the total employment in the area. In other words, it is the result of dividing the number of employees in innovation (I2) by the total number of employees within each Innovation District.
- (%) Sales from innovation (O1): Percentage of the total sales corresponding to innovation.
- Sales from innovation per employee (O2): How much an Innovation District earns from innovations per employee per year.

Although one may think of a high correlation between I2 and I3, each variable presents different information and are not correlated. The correlation between I2 and I3 is negligible (0.087). Fig. 1 displays the model structure.

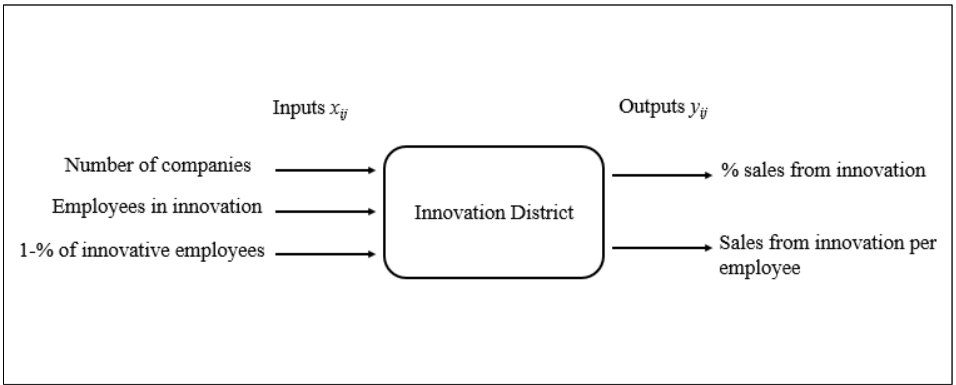

Figure 1 – Data Envelopment Analysis model structure

Tab. 1 summarizes the descriptive statistics of the selected variables for the DEA model, whereas Appendix in the appendix presents the complete dataset for the analysis. The 25 selected Innovation Districts include five different kinds based on the type of anchor institution, which shapes the district's characteristics and affects how people experience their surroundings. The innovation districts include four Entrepreneurial, which are developed where entrepreneurs and start-ups come together in a dense environment; five Industry Clusters, which are the ones growing around dominant corporations; five Local Government, which are developed in regions where government agencies are key drivers of innovation; six Research & Academia, grown around world-class universities; and five Strategic Governmental, which are developed by national research centres (Burke and Gras, 2019).

Table 1 – Descriptive Statistics of the Data Set

		Max	**Min**	**Average**	**Std.Dev.**
Inputs	I1	40,384.00	29.00	3,131.44	7,912.20
	I2	134,152.00	2,384.00	27,703.56	35,584.81
	I3	0.82	0.04	0.53	0.24
Outputs	O1	0.74	0.01	0.31	0.21
	O2	507,033.00	4,843.00	163,808.60	127,016.02

3 RESULTS

3.1 Innovation Districts' Technical Efficiency

Tab. 2 summarizes the obtained results for the 25 Innovation Districts. The average technical efficiency was 0.659, with a standard deviation of 0.311. Aerospace Cluster, Ames Research Center, Boeing Aerospace Cluster (WA), Boulder Innovation District, Google Software Cluster, Silicon Valley, Oak Ridge National Laboratory, Research Triangle Park, and SpaceX Aerospace Cluster reached a technical efficiency of 1.000. On the other hand, the lowest efficiency was acquired by Pittsburgh Innovation District (0.113), Purdue Innovation District (0.119), and Cortex Innovation Community (0.203).

Considering the type of these Innovation Districts, the highest technical efficiency was observed in the case of the Entrepreneurial type (0.831), followed by the Industry Cluster (0.820), Strategic governmental (0.711), and Research & Academia Innovation Districts (0.525). The Local government type registered the lowest technical efficiency (0.468).

The differences obtained could be attributed to the targets of each type of Innovation district. For example, the Entrepreneurial and Industrial Cluster types are business-oriented, and the survival of the companies established within the districts depends on sales and economic success. Whereas, in the governmental districts, business is an essential factor, and they are also concerned about solving social problems that do not necessarily have to do with economic development. Similarly, the Research & Academia Innovation Districts may be focused mainly on proposing solutions for the educational and scientific scopes.

Table 2 – Technical Efficiencies of Innovation Districts and Sensitivity Analysis

DMU	Type	Efficiency Score (Original)	Average	Bias	Mean	Lower bound	Upper bound
Aerospace Cluster	Industry Cluster	1.000	0.698	-0.302	1.000	0.770	1.604
Ames Research Center	Strategic Governmental	1.000	1.000	0.000	1.000	1.000	1.000
Boeing Aerospace Cluster (CA)	Industry Cluster	0.649	0.317	-0.332	0.981	0.729	1.665
Boeing Aerospace Cluster (WA)	Industry Cluster	1.000	0.811	-0.189	1.000	0.615	1.378
Boston Seaport	Local Government	0.671	0.325	-0.346	1.000	0.764	1.692
Boulder Innovation District	Entrepreneurial	1.000	0.656	-0.344	1.000	0.827	1.689
Cortex Innovation Community	Local Government	0.203	0.033	-0.170	0.373	0.346	0.485

DMU	Type	Efficiency Score (Original)	Average	Bias	Mean	Lower bound	Upper bound
Downtown Detroit	Local Government	0.562	0.253	-0.309	0.871	0.659	1.618
Dumbo Innovation District	Local Government	0.474	0.184	-0.290	0.764	0.615	1.456
Google Software Cluster, Silicon Valley	Entrepreneurial	1.000	0.694	-0.306	1.000	0.790	1.613
Harvard Square	Research & Academia	0.486	0.180	-0.306	0.792	0.653	1.440
Houston Medical	Research & Academia	0.899	0.502	-0.397	1.000	0.889	1.793
Jefferson National Accelerator	Strategic Governmental	0.389	0.126	-0.263	0.651	0.548	1.086
Kendall Square	Research & Academia	0.535	0.230	-0.305	0.840	0.645	1.601
Los Alamos National Laboratory	Strategic Governmental	0.227	0.045	-0.181	0.408	0.371	0.562
Microsoft Software Cluster	Industry Cluster	0.453	0.207	-0.246	0.700	0.530	1.492
Oak Ridge National Laboratory	Strategic Governmental	1.000	0.828	-0.172	1.000	0.663	1.345
Pittsburgh Innovation District	Research & Academia	0.113	0.009	-0.103	0.216	0.208	0.246
Purdue Innovation District	Research & Academia	0.119	0.011	-0.109	0.228	0.219	0.264
Research Triangle Park	Research & Academia	1.000	0.745	-0.255	1.000	0.728	1.510
San Jose Boomerang, Silicon Valley	Entrepreneurial	0.750	0.412	-0.337	1.000	0.749	1.675
Sandia National Labs	Strategic Governmental	0.938	0.583	-0.355	1.000	0.851	1.710
Silicon Alley	Entrepreneurial	0.576	0.230	-0.346	0.922	0.742	1.692
South Lake Union	Local Government	0.430	0.153	-0.277	0.707	0.582	1.279
SpaceX Aerospace Cluster	Industry Cluster	1.000	1.000	0.000	1.000	1.000	1.000
	AVERAGE	0.659	0.409	-0.250	0.818	-	-

Notes: The bootstrap efficiency for some DMUs was higher than 1.0. In this case the efficiency is reported as 1.0.

To robust obtained results, the Bootstrap-DEA technical efficiencies were calculated. Tab. 2 presents all the biases for the Innovations Districts, corrected scores (mean), and median and lower and upper confidence interval bounds.

Regarding the corrected scores, the best evaluated Innovation Districts are Aerospace Cluster, Ames Research Center, Boeing Aerospace Cluster (WA), Boston Sea Port, Boulder Innovation District, Google Software Cluster, Houston Medical, Oak Ridge National Laboratory, Research Triangle Park, San Jose Boomerang, Sandia National Labs, and SpaceX Aerospace Cluster. In this case, the highest reported correction of the technical efficiency (bias) can be observed in the Local Governmental Innovation Districts (-0.275) and Research & Academia Innovation Districts (-0.154). On the other hand, the lowest correction can be observed in the Entrepreneurship (-0.091) and Strategic Governmental (-0.101) IDs. Still, the Industry Cluster and Entrepreneurial IDs were evaluated as the best types of Innovation districts (see Fig. 2).

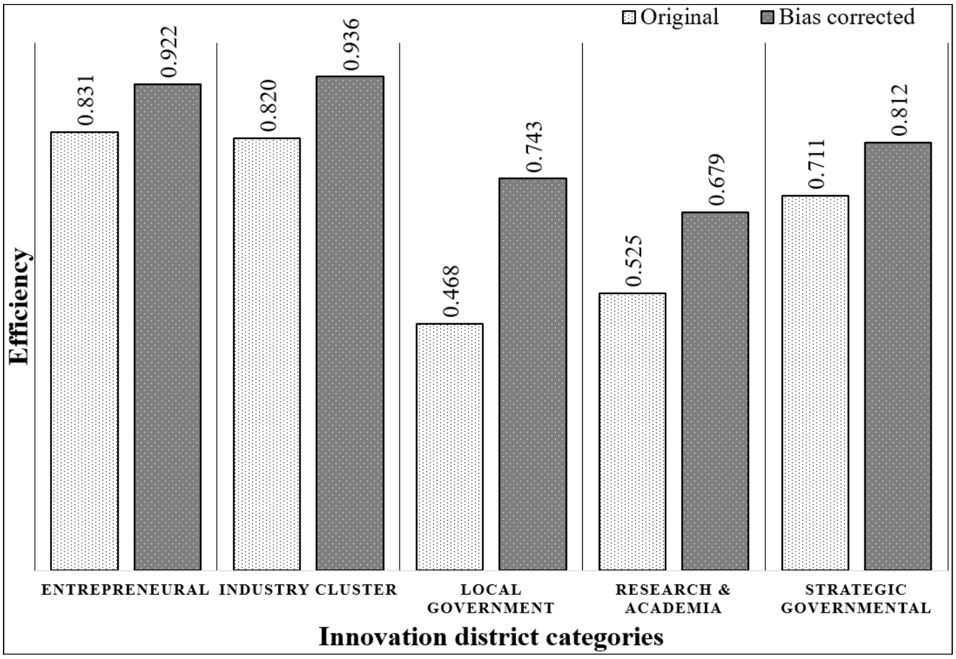

Figure 2 – Original and Corrected Efficiency Scores by IDs Type

3.2 Distrito Tec's Performance Goals

As it was mentioned, Distrito Tec is currently being developed, in Monterrey, Mexico. Tecnologico de Monterrey targets positioning the Distrito Tec among the most prestigious Innovation Districts in the region. That is why it is of high importance to project its outcomes, i.e., to set up performance goals. For obvious reasons, no available data related to % Sales from innovation (O1) and Sales from innovation per employee (O2) exist. However, the information for the inputs already exists (Appendix).

The DEA methodology and the calculated projections for the inefficient DMUs can be used to set performance goals. To do so, we laid the outputs for the

Distrito Tec equal to 0.0001 (to obtain a feasible solution) and included Distrito Tec among the 25 evaluated Innovation Districts.

According to the analysis and the DMUs involved in the model, Distrito Tec must reach a % Sales from innovation (O1) of 0.567 and sales per employee (O2) of $32,582 to reach maximum efficiency. For the % Sales from innovation (O1), the projection is considerably higher than the average; meanwhile, for the sales per employee from innovation (O2), the projection is lower than the average.

These projections may be unreachable during the first years of the Distrito Tec operations. Several combinations of these two variables exist to reach different efficiency levels that could be set as short or mid-term goals. Fig. 3 shows the possible combinations of the outputs to obtain the 50%, 75%, and 100% levels of efficiency score. These values were obtained by iterating the DEA process and adjusting the output variables to get the desired efficiency score. As observed in Fig. 3, the combination proposed by the software is located on the right-hand side of the 100%-score curve (See Fig. 3). This indicates a high percentage of innovation in a low volume of sales. However, as the % of sales from innovation (O1) is significantly higher than the average (0.31), it could be reduced along the curve by increasing the level of sales per employee (O2).

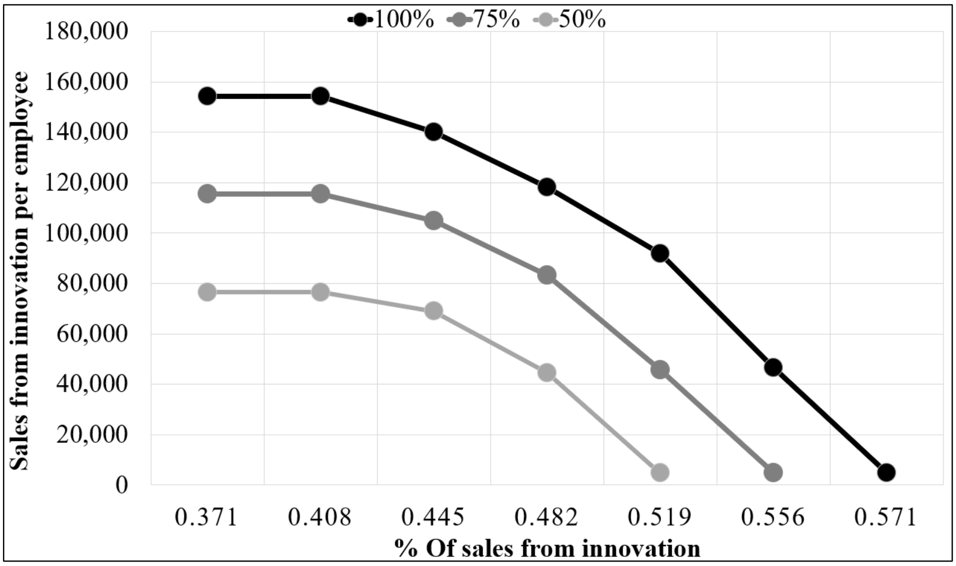

Figure 3 – Output Combinations to Reach Specific Efficiency Scores

4 CONCLUSION

This study's main objective was to determine the goals that Distrito Tec must have in terms of sales from innovation to be comparable to Innovation Districts in the United States. Using DEA and the software MaxDEA the projections for these two variables, (%) of sales from innovation and sales from innovation per employee, were figured out: 0.567 and $32,582, respectively. However, since these values might be a challenge for the young district, some other combinations of outputs were presented to reach different efficiency score levels.

Moreover, it is interesting to figure out that the districts that belong to the Academia and Research category have the lowest performance compared to other districts in other categories. Therefore, it is important for Distrito Tec to have a similar approach to the Industry Cluster and Entrepreneurial Innovation Districts. Etzkowitz (2003) presented the entrepreneurial university concept adopted by Stanford University in California; this strategy consisted of carrying out research with high commercial potential and strong integration between the university and non-academic organizations. In this way, both types of organizations benefit from each other by exploiting the universities' capabilities to create new solutions from research and the commercial strength of companies to transform knowledge into an economic benefit.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

APPENDIX

Input and Output Data for 25 Innovation Districts

District Name	Type	I1	I2	I3	O1	O2
Aerospace Cluster	Industry Cluster	621	4,086	0.292	0.198	348,473
Ames Research Center	Strategic Governmental	29	2,611	0.963	0.531	4,843
Boeing Aerospace Cluster (CA)	Industry Cluster	3,507	33,248	0.467	0.347	209,288
Boeing Aerospace Cluster (WA)	Industry Cluster	1,213	3,450	0.185	0.073	507,033
Boston Seaport	Local Government	1,666	10,505	0.216	0.308	192,461
Boulder Innovation District	Entrepreneurial	1,200	5,908	0.289	0.094	447,092
Cortex Innovation Community	Local Government	1,205	12,138	0.232	0.068	80,542
Downtown Detroit	Local Government	3,928	29,174	0.269	0.411	109,238
Dumbo Innovation District	Local Government	3,253	15,205	0.285	0.246	140,495
Google Software Cluster, Silicon Valley	Entrepreneurial	1,276	26,509	0.676	0.710	252,408
Harvard Square	Research & Academia	1,004	6,884	0.460	0.243	78,046
Houston Medical	Research & Academia	1,887	105,245	0.584	0.666	119,133
Jefferson National Accelerator	Strategic Governmental	1,082	5,621	0.302	0.121	127,238
Kendall Square	Research & Academia	2,097	29,349	0.589	0.382	128,758
Los Alamos National Laboratory	Strategic Governmental	447	11,916	0.687	0.144	30,645
Microsoft Software Cluster	Industry Cluster	663	42,736	0.857	0.280	39,484
Oak Ridge National Laboratory	Strategic Governmental	122	10,592	0.669	0.484	112,751
Pittsburgh Innovation District	Research & Academia	1,052	40,999	0.479	0.006	38,339
Purdue Innovation District	Research & Academia	301	16,290	0.844	0.033	10,732
Research Triangle Park	Research & Academia	554	17,713	0.739	0.741	166,654
San Jose Boomerang, Silicon Valley	Entrepreneurial	6,906	108,748	0.627	0.454	208,233

District Name	**Type**	**I1**	**I2**	**I3**	**O1**	**O2**
Sandia National Labs	Strategic Governmental	557	4,907	0.256	0.481	84,598
Silicon Alley	Entrepreneurial	40,384	134,152	0.197	0.171	240,726
South Lake Union	Local Government	2,977	12,219	0.260	0.149	167,585
SpaceX Aerospace Cluster	Industry Cluster	355	2,384	0.352	0.324	250,420
Distrito Tec	Research & Academia	210	5200	0.21	-	-

Notes: I1 – Number of companies; I2 – Employees in innovation; I3 – (%) Innovative employment; O1 – (%) Sales from innovation; O2 – Sales from innovation per employee.