The impact of Smart Specialization Strategies on Sub-Cluster Efficiency: Case of Mexico

Viviana Elizabeth Zárate-Mirón[1] & Rosina Moreno Serrano[2]

Abstract

The concept of clusters has been popularized over the last two decades, mainly through the work of Michael Porter. A question that has arisen recently in relation to cluster theory is whether it can be complemented with Smart Specialization Strategies (S3). This study applies data envelopment analysis (DEA) to the Mexican economy to evaluate three effects: 1) whether the kind of policies envisaged through a S3 strategy has an impact on the efficiency of Mexican clusters; 2) whether this impact changes with the technological intensity of the clusters; 3) to what extent such impact is related to the technological intensity of the cluster. The results show that strategies following the S3 had a significant impact in all clusters, but when clusters were classified by technological intensity, the impact on efficiency is higher in clusters in the medium low-tech group. According to the results in the DEA, we can conclude that these S3 strategies have the potential to increase the clusters' productivity significantly.

Keywords: Data Envelopment Analysis, clusters, Smart Specialization Strategy, technical efficiency, productivity**.**

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[1] Center for Research and Economic Intelligence, UPAEP University (21 sur #1103, Barrio de Santiago C.P. 72410, Puebla, México): vivianaelizabeth.zarate@upaep.mx

[2] Regional Quantitative Analysis Group, University of Barcelona (Tower IV, Av. Diagonal 690, 08034 Barcelona): rmoreno@ub.edu

1. Introduction

In the last two decades the cluster concept has become popular, but it represents the evolution of ideas that originated at the end of the nineteenth century (Vorley, 2008; Aranguren & Wilson, 2013). Cluster theory is rooted in Marshall's work on "industrial districts" in the books *Principles of economics* (1890) and *Industry and trade* (1919). Marshall defined an industrial district as an area with a high concentration of firms specializing in a main industry and auxiliary industries. Marshall observed that the co-location of firms in an industrial district has more advantages than aggregating activities within a single large firm. Although Marshall's work does not refer specifically to clusters, the empirical work established the fundamental ideas on which it is based.

Since Marshall's time cluster theory has gone through several stages in its evolution (Vorley, 2008). The most recent conceptualization was presented by Porter in the middle and late 1990s. He popularized the concept of cluster theory through his textbook *The competitive advantages of nations* (Porter, 1990) and two articles that became the primary references in this academic field (Porter, 1998, 2000). Unlike Marshall, Porter did not just analyze the macroeconomic effects of localized industrial organizations, but also the microeconomic strategies of firms.

The concept of cluster theory continued to evolve and new approaches were introduced. One of the new questions that have arisen is related to the recent innovation policy called Smart Specialization Strategies (S3). The origin of S3 lies in the clear productivity gap that has existed between the United States and Europe since 1995 (Ortega-Argilés, 2012). A group of experts, called "Knowledge for Growth" (K4G) was established with the purpose of devising a strategy to close this gap. They suggested the S3 whose objective is building competitive advantages in research domains and sectors where regions have strengths. This innovation policy gained significant momentum in 2013 when it was adopted by the European Commission's Science and Knowledge Service. Table 1 summarizes the definition of the S3.

Table 1 Definition of Smart Specialization Strategies

National/regional research and innovation strategies for Smart Specialization (RIS3 strategies) are integrated, place-based economic transformation agendas that do five important things:

- They focus policy support and investments on key national/regional priorities, challenges, and needs for knowledge-based development.
- They build on each country's/region's strengths, competitive advantages and potential for excellence.
- They support technological as well as practice-based innovation and aim to stimulate private sector investment.
- They get stakeholders fully involved and encourage innovation and experimentation.
- They are evidence-based and include sound monitoring and evaluation systems.

Source: European commission, 2013.

S3 is related to cluster policy because both have essential points in common: 1) they both focus on productivity and innovation as key drivers of competitiveness; 2) both argue that there are advantages to proximity between industries (Pronestì, 2019). On the other hand, their differences can make them complementary to each other. "The full potential of clusters and cluster policies will be reached if: The Smart Specialization Strategies integrate cluster policies into a broader transformation agenda for the entire regional economy, and complement cluster policies with other cross-cutting and technology/knowledge domain-specific activities (European Commission, 2013, p.4)". Some authors talk about the possible complementarity between these two innovation policies (Aranguren & Wilson, 2013; Pronestí, 2019).

For this reason, this paper aims to evaluate whether the integration of S3 elements into clusters has a significant impact on their efficiency. In order to reach this goal, variables that represent the S3 elements are included in Porter's clusters classification and we evaluate its impact on efficiency in the year 2013. Data correspond to the Mexican economy because the industries are already classified into Porter's cluster definition. This cluster classification has been already implemented in another study (Mendoza-Velazquez et al., 2018). Although the S3 has not been implemented in the Mexican economy, there are some variables that could be used to represent the S3 elements in order to estimate their impact on clusters. The analysis of these variables could be used to support the design and implementation of the S3 strategy in Mexico. It allows to identify which S3 elements are more effective, and how to improve their performance.

The case of Mexico is interesting because of its stage of development. McCann and Ortega-Argilés (2015) pointed out that, in leading knowledge regions, the S3 argument will be less relevant as almost all sectors and technological fields will be present. On the other hand, S3 should be very well suited to intermediate regions, because of their growth potential and the concentration of possibilities offered by their spatial structure (urban and rural areas). The Global Competitiveness Report (Schwab, 2018) classified countries into three categories according to their stage of development: 1) Factor-driven: natural resources and unskilled labor drive the economy; 2) Efficiency-driven: countries develop more efficient production processes; 3) Innovation-driven: the most sophisticated production processes and innovation processes are used in industry. Mexico is classified as being in the second stage, so it offers an interesting opportunity to investigate whether the efficiency of clusters can be improves by applying S3 strategies in a country that is not a leader in the development of new technologies, and how S3 should be adapted to the technological level of such countries.

Given this background, the aims of this study were: 1) to analyze the general effect of applying S3 across all sub-clusters; 2) to determine whether the effect of S3 varies according to the technological intensity of the sub-cluster; 3) to determine which S3 is more suitable for sub-clusters at different levels of technological intensity. To achieve these goals the paper is structured as follows. The next section summarizes the most important research on the joint application of S3 and clusters. The literature on this topic is not extensive because S3 has only recently been implemented, hence the need for research that provides quantitative evidence on this topic. After the literature review, we describe the method we used, data envelopment analysis (DEA), the reasons for choosing this method and the rationale for our estimation strategy. After the methodology, we present the composition of the clusters and the variables that represent S3 strategies. This is followed by the results of the analysis of how S3 affect sub-cluster efficiency; we present estimates for different sets of models and group of sub-clusters. Finally, we present our conclusions.

2. Literature Review

As the S3 approach was only introduced in 2013 there is not an extensive literature on the topic. First, there is a group of papers dealing with the definition and limitations of S3. McCann and Ortega-Argilés (2015) examined the S3 concept and explained the application challenges. They pointed out that S3 policy recommendations would need to be very different in different places, differing according to the technological profile, industrial structure and geography of the region concerned. They concluded that S3 would be very well suited to intermediate regions because of their growth potential and spatial structure. Piirainen et al. (2017) questioned the different paths for reaching S3 within the same industrial domain. Based on an analysis of the empirical cases of the offshore wind services sectors in four regions around the North Sea, they concluded that there are four distinct patterns of S3: diversification, transition, radical foundation and modernization. Krammer (2017) pointed out that S3 methodologies should consider the particular characteristics of developing countries, such as low entrepreneurship rates and limited technological opportunities. Based on an analysis of the industries in Bulgaria Krammer concluded that S3 will work in the less developed countries so long as they are able to identify the industries where it has the greatest potential. Balland et al. (2018) constructed a policy framework for S3 that highlights its potential risks and rewards. From an analysis of EU regions they concluded that the potential risk of S3 can be represented by the concept of relatedness, and the potential benefits can be derived from estimates of the complexity of technologies.

There is another group of papers about the methods used to identify industries to which S3 can profitably be applied: Gulc (2015) compared the methodological approaches used to identify S3 in Polish regions, concluding that the qualitative method was most popular but not complemented by the quantitative ones. Gonzalez et al. (2017) described and analyzed the location of industrial complexes for the construction of industrial policies based on the principles of related variety and S3.

The brief literature on S3 contains just a few papers on the integration of S3 and the cluster concept. The first reference is a document produced by a group of experts in clusters and published by the European Commission (2013), which identifies the commonalities and differences between them in order to determine the potential contribution of clusters to the design and implementation of S3. This report makes clear, however, that a deeper analysis is required: "since both are policy approaches with a place-based dimension that aim at economic growth and competitiveness, the question of the differences, similarities, and contribution of one approach to the other, is highly relevant (European Commission, 2013, p. 7)".

As well as the European Commission's report there are two papers supporting the idea of integrating S3 and clusters through the study of cases. Aranguren and Wilson (2013) presented the case of the Basque Country, which has two decades of experience in the design of cluster policy. Aranguren and Wilson carried out qualitative analysis to identify the differences and similarities between their mapping cluster and the S3 characteristics mentioned in Foray et al.'s (2012) document. They identified specific points of S3 that contribute to their cluster classification: 1) forms of cooperation among firms and a range of other agents that are developing related or complementary economic activities; 2) processes of prioritization and selection that combine top-down and bottom-up forces; 3) building from existing place-based assets and capabilities. Scutaru (2015) presented a case study of Romania in which clusters were evaluated to determine which had most potential for the development of a S3 plan. The main criterion was the availability of sufficient specialized human capital to support innovation. Bečić and Švarc (2015) analyzed Croatia's clusters and concluded that S3 is better suited to developed countries than developing ones due to the technological backwardness and lack of resources for R&D and advanced technologies.

Todeva (2015) also analyzed the integration of these cluster and S3 policies based on a study of the specific cluster of health technology in the Greater South East of England. This author focuses on a specific characteristic of S3: the combining of the efforts of public administration agencies, business leaders and university establishments. The interaction between these organizations is referred to as the *Triple Helix*. Then, the location of the best health technology cluster for S3 is based on this characteristic.

The smart guide to cluster policy (European Commission, 2016) is a very recent document published by the European Commission. Unlike the European Commission publication mentioned above, this one promotes transition towards modern cluster policies, because the systemic and strategic vision needed for modern cluster policy can be provided by the concept of Smart Specialization. The *Guide* also asserts that existing governmental innovation policies could, in many cases, be made significantly more effective by organizing them around S3 and clusters.

The most recent reference on clustering is a book entitled *The life cycle of clusters in designing smart specialization policies* (Pronestí, 2019), which explores a new perspective on the role of clusters in catalyzing the effective design and implementation of S3. It explains how the different phases of the cluster life cycle (CLC) can help to identify a region's potential to specialize in new domains. Different phases of the CLC have different roles in S3 policymaking. This research showed that a cluster in the stage of emergence, development and transformation offers the best conditions for the entrepreneurial discovery process. To sum up, Pronestí (2019) shows that clusters are useful in the implementation of S3.

Despite the valuable contribution of these authors to understanding of the relationship between clusters and S3, the academic debates about the effective integration of these policies continue. There is a great need for research on this topic, which has been dominated so far by qualitative rather than quantitative analysis. It is fundamental to get estimates that demonstrate the relationships between the two approaches. We aimed to go one step further and investigate whether S3 affects clusters' efficiency, and if so, whether the influence varies according to the technological intensity of the cluster.

3. Methodology

Our first objective was to generate a measure of efficiency. It is essential to start with a definition: efficiency means getting the highest possible level of output for a given amount of inputs and technology. It is important to focus on efficiency because it is one parameter that contributes to variation in productivity[3]. S3 and clusters were created to increment productivity, so if applying S3 increases clusters' productivity, the objectives of both policies are achieved.

To obtain a measure of efficiency it is necessary to compare actual performance with optimal performance, but as it is not possible to know what constitutes optimal performance it is approximated by the "best practice frontier." There are two methods to estimate efficiency: the econometric approach and mathematical programming techniques. The econometric approach is stochastic; it can be implemented using maximum likelihood estimation or corrected OLS (COLS) (Rogers & Rogers, 1998). On the other hand, the programming approach is nonparametric. DEA is the representing methodology in this category.

All the methods have advantages and disadvantages. The choice depends on the research objective and characteristics of the data. One of the main advantages of DEA is that it can handle multiple inputs and outputs (denominated in different units) in a non-complex way (Diaz-Balteiro et al., 2006). Furthermore, Costa et al. (2015) showed DEA estimate of efficiency scores (non-parametric) are more accurate than OLS estimates (parametric). They evaluated the operational efficiency of power distribution companies in Brazil through these methods. After a statistical comparison of the results in both cases, they concluded that the COLS Cobb-Douglas model has major deficiencies as a method of estimating efficiency scores.

Many studies have applied DEA to compare the efficiencies of manufacturing industries. For instance, Zhao et al. (2016) and Chen and Jia (2017) evaluated the efficiency of industries with respect to environmental issues. They included two kinds of variables, those representing the production function and those related to the environment and pollution. Both models include the fundamental inputs to a production function (labor and capital). The output is represented by the value of production or the gross domestic product. DEA has also been used to evaluate innovation in firms and industries (Si & Qiao, 2017; Suh & Kim, 2012; Zhang et al., 2018). In these cases, patents represent the desirable output variable. These examples are relevant to our study because S3 are in essence innovation actions directed at specific objectives.

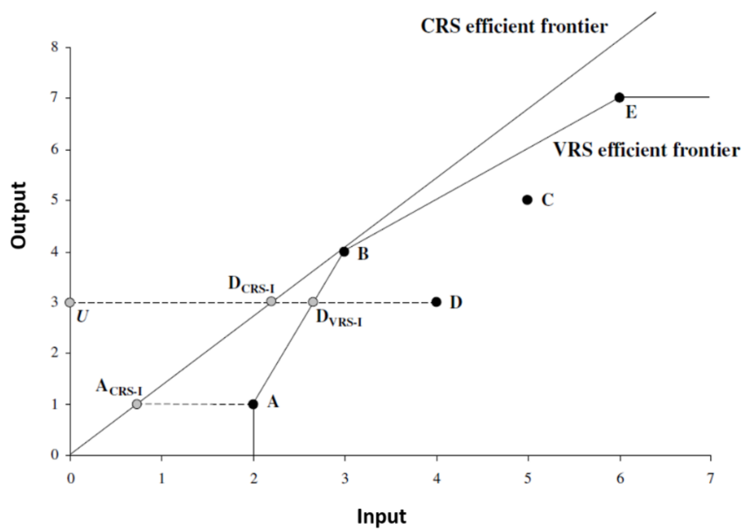
We used DEA, which is a non-parametric technique, to measure the relative rather than absolute efficiencies of decision-making units (DMUs). DMUs can be firms, industries or countries. It does not require to assume any functional form. Although DMUs on the efficient frontier have a 100% efficiency score they could improve their productivity further (Huguenin, 2012). Linear programming methods are used to compute the efficient frontier from inputs and outputs. There are two main DEA approaches: 1) the Charnes, Cooper and Rhodes (1978) approach (CCR) assumes constant returns to scale (CRS) in order to estimate a global efficiency score, which is appropriate when all firms operate at the optimal scale; 2) the Banker, Charnes and Cooper (1984) approach (BCC) uses variable returns to scale (VRS) to estimate a pure technical efficiency score. Both approaches can be implemented in output-oriented models or input-oriented models. The former maximize the output for a fixed input, whereas the latter minimize inputs whilst holding output constant (Banker et al. 1984).

[3] The variation in productivity is a residual that can be attributed to the following reasons (Fried et al., 1993): differences in production technology, differences in the scale of operation, differences in operating efficiency, and differences in the operating environment in which production occurs.

The choice depends on the variables (inputs or outputs) over which the decision-maker has most control or on the objectives of the analysis (Yang, 2006).

To demonstrate the rationale underlying DEA analysis, Figure 1 shows a simple example of efficiency scores estimation with just one input and one output (Huguenin, 2012). Axis “x” represents the input and the axis “y” the output. Each point in the figure represents one DMU with a different combination of input and output. The line 0B represents the efficient frontier for the CCR model under CRS. Meanwhile, the line ABE is the efficient frontier for the BCC model assuming VRS. A DMU is considered efficient if it lies on the efficient frontier. In the case of the CCR model, point B is globally efficient both in terms of management (as signaled by the VRS efficient frontier) and scale (as signaled by the CRS efficient frontier). On the other hand, ABE are efficient DMU’s for the BCC model. The rest of the DMUs (C and D) are inefficient for both cases.

Figure 1 DEA model with one input and one output variable



Source: *Data envelopment analysis (DEA).* Huguenin, 2012

The gap between the CCR (CRS) and the BCC (VRS) frontiers is due to a problem of scale. For instance, A needs to modify its scale (size) to become CRS-efficient. D not only has a problem of scale; it is also poorly managed. First D has to move to the point DVRS-1 to eliminate the inefficiency due to poor management. These two movements represent the components of efficiency: technical (due to management efficiency) and allocative (due to scale efficiency) (Diewert and Lawrence, 1999). Then, D has to move to point DCRS-I to eliminate the inefficiency due to a problem of scale. Observe that, even when D reduces its level of inputs, it still gets the same level of output. The objective of a DEA is to minimize the number of inputs required to maintain a fixed level of output.

The previous example is the simplest way to understand how DEA works. However, in a model with multiple inputs and outputs, the solution to this problem is formulated like a linear programming problem. The following equations represent the input-oriented model for the CCR model (Huguenin, 2012), where *s* is the number of outputs; *m* is the number of inputs; n is the number of units to be evaluated (DMUs); x_{ik} represents the amount of input i consumed by the unit that is evaluated, unit *k*; x_{ij} represents the input quantities i (i= 1, 2,…,*m*) consumed by the *j*th unit (notice that this element is next to a summation operator); y_{ik} is the quantity of output i produced by the unit *k*; y_{ij} represents the observed quantities of output *r* (*r* = 1, 2, …, s) produced for the jth unit (this element also goes with a summation operator); θ_k is the relative technical efficiency score of the *k*th unit; λ_j expresses the weight that each DMU has within the comparison group; ε is a non-negative infinitesimal number for keeping coefficients of input and output variables positive; s_r^- and s_r^+ are non-negative slack variables for input and output constraints.

More details are needed to understand the meaning of the weights and slacks. This last one is the amount deviated from the efficient frontier. The terms $\sum_{j=1}^{n} \lambda_j x_{ij}$ and $\sum_{j=1}^{n} \lambda_j y_{rj}$ are called input virtual and output virtual respectively. These values express information about the importance that a unit attributes to specific inputs and outputs in order to obtain its maximum efficiency score. It is possible to determine the importance (contribution) of each input to the total as well as the contribution of each output to the efficiency score. On the other hand, the slack variables represent potential improvements. They relate to the further increases in output (s_r^+) or reductions in the input (s_r^-) that would be needed to reach the efficiency frontier. In other words, the slack variables can be interpreted as the output shortfall and input overconsumption relative to the efficient frontier. A unit is considered technically efficient if and only if θ*= 1 and all the slacks are null (s_r^-= 0, s_r^+= 0). This means the unit is efficient in relative to the others since it is not possible to find another unit that obtains the same or greater output of that unit using fewer factors. In all other cases a unit is classified as inefficient.

$$Minimize\ \theta_k - \varepsilon \textstyle\sum_{r=1}^{s} s_r^+ - \varepsilon \sum_{i=1}^{m} s_i^-$$

$$Subject\ to$$

$$y_{rk} - \sum_{j=1}^{n} \lambda_j y_{rj} + s_{rk}^+ = 0 \qquad r = 1, \ldots, s$$

$$\theta_k x_{ik} - \sum_{j=1}^{n} \lambda_j x_{ij} - s_{ik}^- = 0 \qquad i = 1, \ldots, m$$

$$\lambda_j, s_r^+, s_i^- \geq 0 \ \ \forall\, j = 1, \ldots, n;\ \ r = 1, \ldots, s; i = 1, \ldots, m$$

The CCR model implies the existence of constant returns to scale. It means that all units are compared and their differences in operational scale are not taken into consideration. It can, however, be used to obtain a model with variable returns to scale. The following equations present the BCC input-oriented model (Huguenin, 2012). Compared with the CCR model, it has an extra constraint $\sum_{j=1}^{n} \lambda_j = 1$, which is a convexity constraint (Figure 1 makes clear the need for this condition). It tells the model that each unit has to be compared with those of the same size rather than with all the units present in the problem. The solution of this system gives, as a result, the pure technical efficiency score of the *k*th unit (φ_k). Compared with using technical efficiency (θ_k), l it is possible to get a higher number of efficient units using the BCC model, because units are compared only with those of the same size.

$$Minimize\ \ \varphi_k - \varepsilon \sum_{r=1}^{s} s_r^+ - \varepsilon \sum_{i=1}^{m} s_i^-$$

$$Subject\ to$$

$$y_{rk} - \sum_{j=1}^{n} \lambda_j y_{rj} + s_{rk}^+ = 0 \qquad r = 1, \dots, s$$

$$\theta_k x_{ik} - \sum_{j=1}^{n} \lambda_j x_{ij} - s_{ik}^- = 0 \qquad i = 1, \dots, m$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j, s_r^+, s_i^- \geq 0\ \ \forall\, j = 1, \dots, n;\ \ r = 1, \dots, s; i = 1, \dots, m$$

The results of this minimization problem can be classified into two groups: DMUs with an efficiency score equal to 1 (100%) that are located at the frontier and inefficient DMUs whose score is less than one (less than 100%) that are located below the efficient frontier. The magnitude of the inefficiency depends on how far the DMU observation is from the efficient frontier (Charnes et al., 2013).

It is necessary to check the robustness of any DEA to outliers. To do this we used a computational approach to detect outliers. It is based on the concept of leverage. The leverage for a single DMU is a measure of the impact that removing one of the DMUs has on the efficiency scores of all the other DMUs (Zhu, 2001). A super-efficient model looks for extreme points with a level of efficiency that can be unrealistic for the rest of the DMUs. The leverage of the *j*th DMU is defined as a standard deviation (Martínez-Núñez & Pérez-Aguilar, 2014). First, the DEA model is estimated from the complete database to obtain the efficient DMUs $\{\theta_k | k$=1, 2,

…, K}. Then, DMUs are removed from the data in turn to generate the new set of efficient DMUs $\{\theta_k^*|k=1, 2, \ldots, K; k \neq j\}$.

$$l_j = \sqrt{\frac{\sum_{k=1\ k\neq j}^{K}\left(\theta_{kj}^* - \theta_k\right)^2}{k-1}}$$

This estimation allows us to get efficiency scores bigger than one. For this reason, it is called a super-efficient model. As a rule of thumb, DMUs that get efficiency scores greater than two are excluded from the estimations (Avkiran, 2007).

4. Variable Selection and Data Description

4.1 Data Source and Clusters

The data source for this study was the National Institute of Statistics and Geography (INEGI) in Mexico. The data were taken from the last Economic Census (2014), which included an exclusive survey of "Science, Technology, and Innovation". The variables were obtained at the national industry level and the most disaggregated level, six digits in the North American Industry Classification System (NAICS). However, to answer the research questions of this paper, these industry observations were classified into clusters. As mentioned in the Introduction, we used the cluster classification system suggested by Porter et al. (2015).

The Porter's definition of a cluster only covers traded industries, whose localization depends on issues of competitiveness. The algorithm that defines the clusters measures inter-industry linkages based on the three distinct drivers of agglomeration: co-location patterns, input-output links and similarities in employment patterns. Applying Porter's algorithm to the Mexican economy generates 51 clusters and 185 sub-clusters. So, it is essential to point out that the cluster's classification and the consequent analysis are sectorial oriented instead of geographically-based. The models reported in this paper were estimated at the sub-cluster level to maximize the number of observations, so the DMU was the sub-cluster. The table in the Appendix shows a complete list of clusters and sub-clusters with the number of industries and firms in each. The total number of firms was 657, 973 classified in 551 industries, 182 sub-clusters, and 51 clusters. The average number of firms in each sub-cluster was 3,654. See Table A1 in the Appendix for a detailed list of clusters and sub-clusters.

4.2 Input/Output Selection

We used the Pastor test (Pastor et al., 2002) to determine whether introducing new inputs or outputs to a model contributes significantly to efficiency. Models are estimated twice, first with the variable of interest included (total model), and second, when it has been excluded (reduced model). The variable is considered relevant if more than a certain share (P) of DMUs have an associated change in efficiency greater than ρ. Following Pastor et al. (2002), the values selected are P=15% and ρ=10%. The null hypothesis is that excluding the variable will lead to a random improvement in the total model. It is evaluated with a binomial statistical test

(Nataraja & Johnson 2011). The candidate variable is not included in the model if the test statistic leads to the rejection of the null hypothesis. The Pastor test can be used to evaluate the contribution of a single variable or a group of variables and Nataraja and Johnson (2011) demonstrated that it performs moderately well under both scenarios. Studies that have applied the Pastor test include Lovel and Pastor (1997), Mancebon and Molinero (2000), Matthews (2013) and Martínez-Núñez and Pérez-Aguilar (2014).

Our data set included seven input variables: (1) employees, (2) capital, (3) presence of collaborative innovation initiatives involving universities and research centers, (4) presence of collaborative innovation activities involving companies without productive relationship, (5) presence of innovation activities in partnership with customers or suppliers, (6) presence of innovation activities in collaboration with the government and (7) investment in research and development for innovation. All variables were measured at the sub-cluster level. Table 2 presents the summary statistics for all of them. There are various rules for determining the minimum number of observations required for a DEA model. In this case, the number of observations (185) was much higher than the minimum number suggested by all of them[4]. All S3 input variables were introduced with a one-year lag because the outcome of innovation activities is not observed immediately[5]. Table 2 shows that some of the variables had a widely scattered distribution (large standard deviation). This is why it is important to carry out super efficiency estimates to check the robustness of the results to the presence of outliers.

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[4] The rules of thumb for the minimum number of observations required for a DEA model with 7 inputs and 2 outputs are: a) At least twice the number of inputs and outputs (Golany & Roll, 1989). According to this rule, we would need 18 DMUs; b) Three times as many DMUs as there are input and output variables, (Sinuany-Stern & Friedman, 1998), DMU=27; c) Twice the product of the number of input and output variables (Dyson et al., 2001), DMU=28

[5] Wang et al. (2016) test the time lags effects of innovation input on output in the national innovation systems in China. They demonstrate that it is not just necessary to lag those variables, but also the distribution of time lags varies according to the characteristics of the innovation input and influencing factors in the internal transformation. The variables included in their study are industry-academy research collaboration, R&D expenditure, and researchers in R&D and are lagged differently. Their variables are quite similar to the ones included in this analysis. Unlike their work, the available database for our study allows only lagging each innovation variable just one year.

Table 2 Summary statistics of outputs and inputs
(Data correspond to the 185 sub-clusters)

Variable	Descriptive Statistics	Unit of measurement	Mean	Minimum	Maximum	Standard Deviation
y_1	Value added, 2013	Thousands of dollars	1,759,004.75	456.07	70,159,482.93	5,752,917.77
y_2	Subcluster patents[a], 2013	Number of patents	15.73	0	115.00	21.96
x_1	Employment, 2013	Persons	50,040.25	127.00	946,966.00	95,047.49
x_2	Capital, 2013	Thousands of dollars	2,521,926.37	387.86	133,840,417.38	11,370,636.40
z_1	Innovation universities[b], 2012	Number of firms	8.38	0	222.00	18.50
z_2	Innovation firms[c], 2012	Number of firms	7.01	0	198.00	16.64
z_3	Innovation clients[d], 2012	Number of fimrs	14.08	0	139.00	23.10
z_4	Goverment innovation[e], 2012	Projects #	2.62	0	24.00	3.13
z_5	Innovation investment[f], 2012	Thousands of dollars	5,850.57	0	116,501.41	13,408.14

Note:
a. Number of firms in the sub-cluster that register patents.
b. Number of firms in the sub-cluster that register innovation activities in collaboration with universities, 2012
c. Number of firms in the sub-cluster that register innovation activities in collaboration with other firms, 2012
d. Number of firms in the sub-cluster that register innovation activities in collaboration with clients, 2012
e. Number of firms in the sub-cluster that register innovation activities in collaboration with the Government, 2012
f. Investment in research and development for innovation, 2012.

The first two inputs were the traditional ones in a production function. The variable employees is the number of persons working in each sub-cluster. Business Support Services is the sub-cluster with the highest number of employees, 946,966, which is equivalent to 10.2% of the total labor force in the clusters. Forestry had the fewest employees, with 127. Capital was measured in thousands of dollars. It is interesting to notice that the three sub-clusters with the highest levels of capital are related to the production of energy: Electric Power Generation and Transmission, Oil, and Gas Extraction and Petroleum Processing. Together they account for 49% of the total capital.

The rest of the input variables represent the S3 elements. Table 3 summarizes the S3 elements and the way that they are represented in the model. The first element is aiming to get stakeholders involved in innovation activities and it is captured by three input variables: the number of firms in the cluster that carry out innovation activities in collaboration with 1) universities and research centers (innovation with universities); 2) other companies without a productive relationship (innovation with firms); 3) with customers or suppliers (innovation with clients). These three variables can be highly correlated, but this tends not to affect the average efficiency score in DEA (López et al., 2016). As expected, the sub-cluster Colleges, Universities, and Professional Schools had the greatest number of firms carrying out innovation activities in collaboration with others, 9.8% of the total projects. The Construction sub-cluster was in second place, with 4.5% of firms collaborating with other organization on innovation activities.

According to the European Commission (2013), the range of stakeholders to be involved in the implementation of S3 is potentially very wide. However, it is typically focused on the Triple Helix members (Etzkowitz & Leydesdorff, 1995), which refers to the relationship between universities, private industry, and government. For this reason, we represent the first S3 element with the number of firms in the sub-cluster that register innovation activities in collaboration with universities, research centers, and other firms. The government was not included because, by itself, it represents the following component.

Turning back to Table 3, the second key element is implementation of a policy that supports and invests in national/regional priorities, challenges and needs for knowledge-based development. This element is captured as the number of firms in the cluster that have received government funding for a specific project or for innovation activities (government innovation). The government invested in innovation projects in 484 firms in 2012. The three sub-clusters with the highest number of firms that had received funding were Automotive Parts (24), Bus Transportation (21) and Biopharmaceutical Products (14). We can conclude that these sectors are the government's priority when it comes to innovation. The role of the government in the S3 context is to provide incentives and encourage entrepreneurs and other organizations to be involved in identifying the regions' specializations, supported through a targeted investment agenda (European Commission, 2016). During the period 2000- 2012, the Mexican government significantly increase its investment in Science and Technology. The public-private partnership was being encouraged by Strategic Alliances and Innovation Networks for Competitiveness (AERIs) (OECD, 2012). Therefore, this variable represents the public-private partnership envisaged in the S3 strategy.

The third key element of S3 is stimulation of private sector investment to support technology and innovation. This element is represented in the model by the amount invested in innovation in each sub-cluster (investment in innovation). The sub-clusters with the greatest investment in innovation were automotive parts (10.1%), motor vehicles (8.5%) and biopharmaceutical products (4.4%). Although Mexico has not developed an S3 strategy, this variable helps to approximate the effect of investment on innovation.

The data set includes two outputs: (1) value-added and (3) patents. As mentioned in the methodological section, output can be measured as gross output or value added. However, value-added is mainly used in analyses at the industry or firm level (Organization for Economic Cooperation and Development; OECD, 2001). "Value-added is a net measure in the sense that it includes the value of depreciation or consumption of fixed capital" (OECD, 2001, p. 24). Value added was measured in thousands of dollars.

The fourth element in Table 3 points to the need for an evidence-based, monitoring and evaluation system for the S3 innovation strategies. We attempted to create a proxy for this element in the form of an additional output, the number of firms in a cluster that have registered patents. In our dataset there were 2,910 firms that had registered patents, which is equivalent to 0.43% of the total. Considering that the Mexican government incentivized the public-private partnership for innovation, and given the insignificance of private investment on innovation in the Mexican case (OECD, 2008), the number of patents that are registered by sub-clusters must be very likely the result of the public economic support.

Following the Guide to Research and Innovation Strategies for S3 (European Commission, 2012), there is no single standardized approach for developing an evaluation system for a S3, since it needs to be tailored to each specific region. In general, the evaluation should measure a change in the region towards activities globally competitive or with potential for value-added. For more specific objectives, it should be evaluated with different variables in the short and long term. For instance, when the objective for the S3 strategy is an increase of the research activity in a region, which is the case for this study, we can use the number of patents as an intermediate indicator. In the long term, the evaluation should be made based on improving innovation performance and enhanced reputation. Therefore, the information from this guide supports to consider the value-added and the number of patents registered as variables for evaluation.The last S3 key element in Table 3 is building on each country or region's strengths, competitive advantages and potential for excellence. This characteristic is already included in the definition of the clusters. It was mentioned above that Porter's methodology just considers traded industries, whose localization depends on factors relevant to competitiveness (Porter et al., 2015).

Table 3 Variables representing the S3 key elements

Key elements of S3	Representative variable	Measure
1. Getting stakeholders fully involved and encouraging innovation and experimentation	Innovation activities in coordination with universities and research centers.	Number of firms in the sub-cluster that register innovation activities in collaboration with universities, 2012
	Innovation activities in collaboration with companies without productive relationship	Number of firms in the sub-cluster that register innovation activities in collaboration with other firms, 2012
	Innovation activities in partnership with customers or suppliers.	Number of firms in the sub-cluster that register innovation activities in collaboration with clients, 2012
2. Policy support and investments are focused on key national/regional priorities, challenges and needs for knowledge-based development	Innovation activities in collaboration with the Government	Number of firms in the sub-cluster that register innovation activities in collaboration with the Government, 2012
3. There is support for technological as well as practice-based innovation and efforts to	Investment in research and development for innovation.	Thousands of dollars of private investment in each sub-cluster, 2012

stimulate private sector investment		
4. Policies are evidence-based and include provision for sound monitoring and evaluation systems	Industries that register patents	Number of firms in the sub-cluster that register patents.
5. Policies build on each country or region’s strengths, competitive advantages and potential for excellence.	This characteristic is already include in the Porter's cluster definition because it consider just traded industries.	Traded industries are classified in 51 clusters and 185 sub-clusters.

5. Results

This section is divided into two parts. The first describes the testing of the different sets of models to find the most appropriate ones. The second takes the selected set of models to estimate CCR and BCC models in order to provide evidence relevant to our main objective. As commented before, given that the cluster classification was made at the national level, all the results presented in this section are sectorial oriented instead of geographically-based.

5.1 Sensitivity Analysis

Table 4 shows the results of the first set of models. Model 1 is the basic production function with two inputs (labor and capital) and one output (value added). This model was extended with the addition of universities (model 2).The Pastor test showed that the extra variable contributed to the explanation of sub-cluster efficiency. Similarly, the input variables other firms and government, which were added in model 3 and 5 respectively, were also shown to contribute to variance in sub-cluster efficiency (all *p*s significant at the 1% level). These variables were therefore retained in the model. On the other hand, the variables clients (model 4) and investment in innovation (model 6) did not contribute to variance in efficiency.

Results for the second set of models are presented in Table 5. In this set of models patents was treated as the output variable. Once again the variables universities, other firms, and government contributed to variance in sub-cluster efficiency. Unlike the previous set of models, innovation activities with clients also contributed to sub-cluster efficiency, possibly because output is related to innovation, although investment in innovation did not contribute to efficiency.

Previous tables show that most of the inputs have an impact on both output variables. Table 6 considers the two outputs, value-added and patents together. All the inputs contributed to efficiency in this case, except for investment in innovation. This variable was therefore not included in the final model. Doing so caused an increase in the number of efficient DMUs that is not rightful. Consequently, the model selected to test the hypothesis was model 22. We expected the variable picking up the investment in innovation not to have a significant contribution to the efficiency given the lack of privet investment to this issue in Mexico. In 2008, the OECD Review of Innovation Policy indicates that the ratio of R&D expenditures to GDP in Mexico was the second-lowest among OECD countries. Furthermore, despite growing R&D investment by industry, most R&D was performed by the public sector. Therefore, it seems that in the sensitivity analysis the variable government has a significant contribution whereas this is not the case for the variable innovation investment.

Table 4 Results of Pastor et al model selection procedure

		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
y1	Value added	x	x	x	x	x	x	x
y2	Registered patents							
x1	Employment	x	x	x	x	x	x	x
x3	Capital	x	x	x	x	x	x	x
z1	Universities		x					x
z2	Other firms			x				x
z3	Clients				x			x
z4	Goverment					x		x
z5	Innovation investment						x	x
B			120	128	98	163	102	170
T			64.9%	69.2%	53.0%	88.1%	55.1%	91.9%
p value			0.000***	0.000***	0.462	0.000***	0.186	0.000***

B= Number of sub-clusters whose efficiency changes by at least 10% in the new model.
T= Percentage of sub-clusters whose efficiency changes by at least 10% in the new model.
* Significant at the 10%; ** Significant at the 5%; *** Significant at the 1%

Table 5 Results of Pastor et al model selection procedure

		Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
y1	Value added							
y2	Registered patents	x	x	x	x	x	x	x
x1	Employment	x	x	x	x	x	x	x
x3	Capital	x	x	x	x	x	x	x
z1	Universities		x					x
z2	Other firms			x				x
z3	Clients				x			x
z4	Goverment					x		x
z5	Innovation investment						x	x
B			156	155	165	164	104	174
T			84.3%	83.8%	89.2%	88.6%	56.2%	94.1%
p value			0.000***	0.000***	0.000***	0.000***	0.106	0.000***

B= Number of sub-clusters whose efficiency changes by at least 10% in the new model.

T= Percentage of sub-clusters whose efficiency changes by at least 10% in the new model.
* Significant at the 10%; ** Significant at the 5%; *** Significant at the 1%

Table 6 Results of Pastor et al model selection procedure

		Model 15	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21	Model 22
y1	Value added	x	x	x	x	x	x	x	x
y2	Registered patents	x	x	x	x	x	x	x	x
x1	Employment	x	x	x	x	x	x	x	x
x3	Capital	x	x	x	x	x	x	x	x
z1	Universities		x					x	x
z2	Other firms			x				x	x
z3	Clients				x			x	x
z4	Goverment					x		x	x
z5	Innovation investment						x	x	
B			134	137	141	151	100	166	163
T			72.4%	74.1%	76.2%	81.6%	54.1%	89.7%	87.6%
p value			0.000***	0.000***	0.000***	0.000***	0.303	0.000***	0.000***

B= Number of sub-clusters whose efficiency changes by at least 10% in the new model.

T= Percentage of sub-clusters whose efficiency changes by at least 10% in the new model.
* Significant at the 10%; ** Significant at the 5%; *** Significant at the 1%

5.2 Comparison of DEA Results

Model 15 was taken as the base case in the comparison of CCR and BCC results. It includes two inputs (employment and capital) and two outputs (value-added and registered patents). Table 7 shows the results for the CCR and BCC models. In these models the Mexican sub-clusters had an average efficiency of 24.22% or 35.59%[6], depending on whether the model considered CRS or VRS. These numbers indicate that sub-clusters could achieve the same output, in terms of value added or patents, whilst making input savings of 75.78% and 64.41% respectively. Seven of the 185 sub-clusters in the sample were deemed efficient by the CCR model (CRS), and 16 by the BCC model (VRS). In other words, seven sub-clusters are globally efficient, and 16 are technically efficient. That implies that there are nine sub-clusters that become globally efficient by scaling up their activity. The percentage of sub-clusters deemed efficient was 3.79% and 8.65% in the CCR model and BCC model respectively, indicating very high levels of global and operational or management inefficiency in the sub-clusters.

Table 7 Original DEA Efficiency coefficients (model 15)

	CCR	BBC	Scale
# efficient DMUs (Sub-clusters)	7	16	7
% Efficient DMUs (Sub-clusters)	3.79%	8.65%	3.79%
Average Efficiency	24.22	35.59	75.92
Standard deviation	21.14	28.44	23.48
Maximum	100	100	100
Minimum	4.31	4.34	14.79

Table 8 DEA results applying Super Efficiency

	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21	Model 22
# outlier removed [a]	2	3	3	3	3	4	8	4
# efficient DMUs (Sub-clusters)	7	16	18	17	20	23	57	38
% Efficient DMUs (Sub-clusters)	3.83%	8.79%	9.89%	9.34%	10.99%	12.71%	32.20%	20.99%
Average Efficiency	27.25	45.59	46.05	45.54	46.16	41.82	70.25	59.49
Potential input savings (respect to model 15)		18.34	18.80	18.29	18.91	14.57	43.00	32.24
Average Efficiency score of inefficient DMUs	24.36	40.35	40.13	39.93	39.52	33.36	56.11	48.73
Standard deviation	21.52	26.22	25.90	25.15	27.41	28.78	25.95	27.50
Maximum	100	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Minimum	4.62	7.60	7.58	7.80	7.18	8.46	16.66	9.08

[6] In DEA analysis, the maximum magnitude obtained for efficiency is 1 (100%), which corresponds to the units of analysis that reach the frontier. In other words, the unit that registered the most efficient use of their inputs compare to others. An efficiency lower than 100% implies that the unit is inefficient, being below the frontier.

Outliers from the supper-efficiencies.

Table 8 presents the CCR results for models 15 to 22. These results are provided for comparison purposes, because CCR represents global efficiency (in management and scale). The CCR approach, using CRS, provides more conservative estimates of efficiency than the BCC approach, which uses VRS (Cantos et al., 2000. In order to get robust results we used the super-efficiency approach to detect and exclude outliers from the data used for the CCR analysis. The first row of Table 8 shows the outliers removed in each model. A trend can be seen towards an association between efficiency and use of S3 in the sub-clusters. It is evident that average efficiency is higher in the extended models than in the base model (15). The highest average efficiency score was obtained when all the S3 elements were included; this raised average efficiency from 27.25% to 59.49%. When the production process included collaborative innovation activities with universities, the potential input saving was 18.34%, which corresponds to the average efficiency increment from Model 15 to Model 16. Similar percentages were obtained when production included collaborative innovation activities with other firms (18.80%) and clients (18.29%). The highest input saving was observed with the industries in the sub-clusters carrying out innovation activities in collaboration with the government (18.91%). The smallest input saving was for investment in innovation, but this result was expected since this variable failed the Pastor Test.

Based on the Pastor test, the final model selected was model 22, which included all the proposed variables except for investment in innovation. In this model the potential input saving was 32.24%. In other words, the performance of its inputs improves by this ratio. In this case, the average inefficiencies are reduced by 24.4% (average efficiency increase of model 21 with respect to 15). This means that when all S3 variables are included in the production process, the average inefficiency of sub-clusters is reduced by 24.4%. Furthermore, including S3 variables also increased the number of sub-clusters that reach global efficiency (in management and scale) from 7 to 38. More sub-clusters make optimal use of their inputs.

5.3 Results by Technological Intensity

So far, we have not considered how the different technological intensities of sub-clusters could affect the impact of the S3 variables. For that reason, this section presents the results by groups of sub-clusters. First, we separate them according to the classification scheme for technical intensity of manufacturing industries by Eurostat Statistics (2018), which defines four groups of manufacturing industries: high-tech, medium high-tech, medium low-tech and low tech. Services are classified into two groups: knowledge-intensive and less knowledge-intensive. The sub-clusters were assigned to one of these categories based on the kind of industries they contained. For instance, since the pharmaceutical industry is classified as high-tech, the biopharmaceutical products sub-cluster was assigned to that category. Other examples are motor vehicles industries and the motor vehicles sub-cluster in the medium high-tech category; rubber and plastic product industries and Plastic products cluster in the medium low-tech group; textile industries and textile and fabric-finishing sub-cluster in the low-tech category; air transport services and air transportation sub-cluster in the knowledge-intensive services; and business support activities and business support services sub-cluster in the less knowledge-intensive services. To sum up, this process identified 8 high-tech sub-clusters, 34 medium high-tech sub-clusters, 26 medium low-tech sub-clusters, 43 low-tech sub-clusters, 35 knowledge-intensive services sub-clusters and 39 less knowledge-intensive services sub-clusters. For a full list of this classification see Table A1 in the Appendix.

We obtained DEA results for all groups by applying the super efficiency approach. The high-tech and medium high-tech were treated as a single group because high-tech contained just eight sub-clusters, and it is not possible to get DEA results with this number of DMUs. Tables A2 to A6 in the Appendix present the estimations by group. In this section, Table 9 summarizes the results just for models 15 and 22. Remember that model 15 includes the essential inputs in a production function (labor and capital) whilst model 22 also includes the variables that represent S3 strategies.

The results in Table 9 make it clear that S3 strategies have the highest impact on the efficiency of the medium low-tech group: the percentage of sub-clusters that reach global efficiency (in management and scale) increases from 24% to 65.2%. This group also has the highest average efficiency (91.25%). Furthermore, even the inefficient sub-clusters comprising medium low-tech industries obtained the greatest average efficiency score (74.85%). On the other hand, with respect to input saving, S3 had most impact on the high-tech and medium high-tech groups, the performance of their inputs improving by the ratio of 32.35%. Nevertheless, despite the high input saving, the average efficiency and the percentage of efficient sub-clusters were still higher in the medium low-tech group. This can be attributed to the fact the industries in Mexico's high-tech sub-clusters are still developing (which is reflected in the fact that this group was represented by just 8 sub-clusters). Service sub-clusters present similar results to manufacturing; S3 converted a higher percentage of sub-clusters to efficiency in the case of less knowledge-intensive services (38.2%) than the knowledge-intensive service sector (25.8%). It seems that the implementation of S3 offers more advantages in industries and services that have a medium dependence on technology and are less knowledge-intensive.

Some facts allow us to explain the magnitude of the efficiency estimated. First, the results for the base model (Model 15) approximate to the ones obtained in a similar study. Mateo et al. (2014) estimate efficiency for Mexican manufacturing industries through a DEA. They also take into account as a data source the Economic Census, but their analysis corresponds to the year 2008. The inputs considered are labor and capital, while the output is gross production. The results are presented by groups of technological intensity: low tech, medium low-tech, and high-tech. Even when the output variables and the year of analysis are not the same as our study, their results can be considered as a point of reference.

According to Mateo et al. (2014) the average efficiency of manufacturing industries in Mexico was 49.78[7] in 2008. Meanwhile, in our study, the average cluster efficiency is 57.71[8]. The gap between these values could be attributed to the different specifications in each model and the different economic situation in 2008

[7] Mateo et al. (2014 [60]) present the efficiency estimations according to the size of the firms (micro, small, medium, and large). The average efficiency mentioned (49.78) considers all of them except for micro firms. We compare our result with this average because we also did not take into account this firms' size. .

[8] In order to compare our results with the ones in Mateo et al. (2014 [60]), the average of 57.71 considers just the estimations for High-tech and medium High-tech (47.32), Medium low-tech (71.01) and low-tech (54.8).

and 2014. For instance, their research analyzes data before the great recession (2008), and our analysis after the downturn(2014). By technological intensity, the estimations for low tech manufacturing are very similar in both cases. We obtain an average efficiency of 54.8; meanwhile, this value corresponds to 56.33 in the other study. The medium high-tech group shows the highest difference: 71.01 in our study and 34.67 in the other one. In the case of high tech manufacturing, we estimate the average efficiencies of 47.32, compared with 58.33.

Therefore, the significant impact of innovation variables on the base model could be explained by the strategy for science and technology implemented in Mexico. The Mexican government carries out the Special Programme for Science, Technology, and Innovation (PECiTI) in the period 2008 – 2012. This strategy had an ambitious set of objectives as a greater focus on innovation carried out by enterprises and, in particular, by small and medium-size enterprises (SMEs) (OECD, 2012). Apart from this program, the stage of development in Mexico could explain the higher impact of the innovation variables on the medium high-tech clusters. This stage of development is characterized by some gaps in physical infrastructure, restrictive regulations, and low levels of human capital. Therefore, Mexican firms have a preference for imported technologies over the development of domestic capacity (OECD, 2012). They prefer to adopt and adapt those high tech technologies that already exist, which gives place to the fact that the high tech but the medium high tech manufactures are the ones making the innovation effort.

Table 9 DEA results applying Super Efficiency

Sub-clusters groups by technological intensity

	High-tech and Medium High-tech		Medium low-tech		Low-tech		knowledge-intensive services		Less knowledge-intensive services	
	Model 15	Model 22	Model 15	Model 22	Model 15	Model 22	Model 15	Model 22	Model 15	Model 22
# Sub-clusters	42	42	26	26	43	43	35	35	39	39
# outlier removed	1	4	1	3	3	5	1	4	1	5
# efficient DMUs (Sub-clusters)	3	12	6	15	5	14	7	8	8	13
% Efficient DMUs (Sub-clusters)	7.3%	31.6%	24.0%	65.2%	12.5%	36.8%	20.6%	25.8%	21.1%	38.2%
Average Efficiency	47.32	79.67	71.01	91.25	54.80	74.81	53.52	75.48	56.85	76.11
Potential input savings (respect to model 15)		32.35		20.24		20.01		21.96		19.26
Average Efficiency score of inefficient DMUs	43.17	70.29	61.85	74.85	48.34	60.11	41.47	66.95	45.34	61.32
Standard deviation	20.96	21.63	21.80	17.37	28.48	25.74	31.74	25.33	30.89	24.55
Maximum	100	100	100	100	100	100	100.00	100	100	100
Minimum	11.32	25.5	18.64	27.17	17.28	24.54	8.79	16.63	11.85	27.94

Tables A2 to A6 (see Appendix section) present other important results, such as the most effective S3 strategy for each kind of sub-cluster group. For the high-tech and medium high-tech group, the highest increment in the percentage of efficient sub-clusters (from 7.32% to 26.83%) was observed when the variable innovation activities in coordination with universities and research centers (model 16) was added to the model. This is because only high-tech firms can absorb the knowledge provided by the universities, which is of a more fundamental nature and needs to be developed into new processes or new products. In the case of the medium low-tech group, investment in research and development for innovation had the highest impact on efficiency (model 20). The percentage of efficient sub-clusters doubled from 24% to 48%. Firms with this level of technology need to adopt and adapt technology to their production process, making it necessary for them to invest in innovation. In the case of the low-tech group the greatest impact came from the inclusion of innovation activities in collaboration with the government (model 19), which increased the percentage of efficient sub-clusters from 12.5% to 28.21%. Investment in innovation is not one of the main priorities for firms in this group, so perhaps government investment enables them to become involved in innovation activities.

Service sub-clusters present similar results to those of the last two manufacturing groups. For knowledge-intensive services, the most critical S3 element was investment in research and development for innovation, which increased the percentage of efficient sub-clusters from 20.59% to 38.71%. As in the manufacturing group, this S3 is crucial because firms have to adapt and adopt knowledge. For less knowledge-intensive services, however, the most influential variable was innovation activities in collaboration with the government, which increased the percentage of efficient sub-clusters from 21.05% to 31.58%. The development of new knowledge does not occur to a meaningful extent in this group, so it is possible that government resources are required to enable it to innovate.

6. Conclusions and Discussion

This research aimed to provide empirical evidence relevant to the discussion about whether S3 can be considered as a new step in the evolution of the cluster concept. We therefore evaluated the impact of the different strategies envisaged in a S3 on the efficiency of 185 sub-clusters in Mexico using a DEA. The results confirmed that the application of S3-type policies increased sub-cluster efficiency. This indicates that policies addressed to clusters should be complemented with S3 strategies to enable them to make more efficient use of their inputs.

Although policies envisaged in a S3 had a general positive influence, it should be remembered that the effects varied with the technological intensity of sub-clusters. We found that S3 had most impact on the medium low-tech group, producing the greatest increment in the percentage of efficient sub-clusters in this group. This result makes sense in the case of Mexico, a country that is not a leader in the development of new technologies. This finding also contributes to debate on whether S3 implementation should be different in developed and developing countries. Another important observation is that, although S3 had most impact on the percentage of efficient sub-clusters in the medium low-tech group they produced the greatest input saving in high-tech industries.

This study has provided an in-depth analysis of which specific S3 elements are most effective for industries at each technological intensity. The high tech and medium high-tech sub-clusters benefit most from innovation activities in collaboration between firms and universities and research centers. This makes sense, since the most revolutionary innovation depends on highly specialized research. For the medium low-tech group, the most effective S3 was internal investment in research and development for innovation. The main reason could be that firms with this level of technology need to adopt and adapt technology to their production process. Meanwhile, for the sub-clusters groups of low-tech, the key S3 element was innovation activities in collaboration with the government, perhaps because development of new technology is not a priority for this group and is only possible with financial support from government. The results for services were similar to those for the last two manufacturing groups. For knowledge-intensive services, the most important strategy was internal investment in research and development for innovation, whereas for the less knowledge-intensive services it was innovation activities in collaboration with the government. Similar reasons to those given above with reference to the manufacturing groups may apply. All the findings noted here have implications for public policy. The main message is that the technological intensity of sub-clusters should be considered in the design and implementation of an S3 initiative.

This research also contributes to the academic discussion about how to implement the S3 approach. As it has only recently been introduced there is a lack of analytical tools (McCann & Ortega-Argilés, 2015) and empirical evidence (Morgan, 2017; Piirainen et al., 2017) to guide its application. Although this study did not attempt to determine whether clusters are the most appropriate base for applying S3, it sheds light on this option. As noted by Aranguren and Wilson (2013), many countries already use clusters to guide regional development, so they could easily be used to facilitate the design and implementation of S3. In this study we analyzed clusters using Porter's classification, which is amongst the most widely adopted by policymakers.

As well as contributing to the academic literature this study has important implications for public policy in Mexico. As Mexico has not implemented any overall strategy for S3 the results could be used to support design and implementation of such a strategy. We have shown that application of S3 produces a general increase in sub-cluster efficiency, which is one of the main issues on Mexico's political agenda. In recent decades Mexico's growth in productivity has been modest, leading to low and volatile economic growth (Padilla-Perez & Villarreal, 2017). This topic is so important for the Mexican government that some actions have already been implemented, for example a National Commission on Productivity was established in 2013.

The application of S3 in Mexico should focus on the medium low-tech industries. This group includes sub-clusters like metal containers, jewelry, and precious metals products, glass products, and rubber products, among others. It should be remembered that the most effective S3 in this group is investment by firms in research and development for innovation. The design of the S3 policy should include mechanisms to encourage such investment, for example tax rebates for firms that invest in innovation projects. Finally, if Mexico were to adopt an S3-based innovation policy the effects of the variables that represent S3 might become more prominent. We have used some variables from the Economic Census to represent the S3 and shown that they have a positive impact on efficiency.

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