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APPLICATION OF DEA MODEL WITH BOOTSTRAP TO EVALUATION OF SMES EFFICIENCY IN THE SPANISH TEXTILE INDUSTRY

Abstract

The Spanish textile industry underwent an important transformation during the 1990s. To survive under new market conditions, firms had to refocus their competitive strategies towards an increase in productive efficiency or an investment in technological development. The purpose of this paper is to evaluate the technical efficiency in the sample of 66 micro-, small- and medium-sized textile companies that operated in the Spanish region of Catalonia during the 1996-2001 period. Based on the firm-level accounting data we derive efficiency estimates using Data Envelopment Analysis model with bootstrap. The general result of this study shows that firms in the sample are on average relatively highly efficient in their productive process. The bias-corrected efficiency score reaches the 0.817 level and it slightly fluctuates during the period analyzed.

Keywords

Textile industry, efficiency, DEA, SMEs

Introduction

Textile industry in Spain since the 1990s has undergone major restructuring and readjustment in order to improve the competitiveness of companies, which faced the increased competition from low-wage developing countries. As the answer to those competitive pressures, companies had to substantially reduce the mass production and refocus their competitive strategies towards an increase in productive efficiency or an investment in technological development.

Within this context, the aim of this paper is to evaluate the efficiency of Spanish micro-, small- and medium-sized firms (*SMEs*) in the textile industry. We analyze textile firms operating in Spanish region of Catalonia, where they have traditionally been mostly concentrated. In particular, we are interested to analyze if the competitive pressures have impacted the level of companies' efficiency. The empirical part is based on the firm-level data, which consists of accounting information covering the time period of six years: from 1996 to 2001. We use the Data Envelopment Analysis (*DEA*) model for assessing the efficiency of companies and we perform a bootstrap of efficiency scores to derive the confidence intervals and to measure the bias for those indices.

The focus of the study on micro-, small- and medium-sized firms is of particular importance. While firm-level performance and efficiency among larger companies was studied intensively, such research on *SMEs* is rather rare [Hill and Kalirajan, 1993]. In addition, Spanish textile sector is predominantly based on micro-, small- and medium-sized companies [Stengg, 2001].

The paper proceeds as follows. We first describe the evolution of the Spanish textile industry. Then we present the Data Envelopment Analysis model with bootstrap that permits to measure the technical efficiency of firms. The subsequent sections describe the data, the variables and discuss the results. Conclusions are presented in the final section.

1. The textile industry in Spain

The textile sector in the European Union (*EU*) in 2004 represented some 77 288 firms with production of 104 billion euros, while an average firm produced 1.4 million euros[*]. Its importance for social and economic cohesion is increased by the fact that it is dominated by a large number of micro, small and medium-sized companies, which are often concentrated in particular regions contributing greatly to their wealth and cultural heritage [Stengg, 2001]. Spanish textile industry is not an exception. It has traditionally been a major sector in the manufacturing industry. In 2003 its production exceeded 13 000 million euros manufactured in 7200 companies, giving the employment to almost 260 000 people. The Spanish textile industry occupies the fifth place among the *EU-15*[**] countries with the share of 8% of the *EU-15* total, and falls behind Italy (28%), the United Kingdom (14%), France (12%) and Germany (13%) [Stengg, 2001]. The risk factor for the Spanish textile sector is the fact that imports continue to grow dangerously (Table 1).

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[*] According to the European Commission survey *Study on the competitiveness, economic situation and location of production in the textiles and clothing, footwear, leather and furniture industries*.

[**] *EU*-15 refers to the *EU* countries prior to accession of 12 members in 2004 and 2007 that is comprising of Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden and the United Kingdom.

Table 1

Data for Spanish textiles

Data for Spanish textiles	2000	2001	2002	2003
Employment	278 200	277 900	268 200	257 500
Number of firms	7 615	7 590	7 470	7 200
Production (millions of euros)	14 827	14 800	13 912	13 258
Imports (millions of euros)	7 671	8 231	8 620	9 431
Exports (millions of euros)	5 475	5 991	6 143	6 437

Source: [Centre of Information about Textile and Clothing Industry – Centro de Información Textil y de la Confección *CITYC*].

The textile industry in Spain confronts the radical changes posed by the internationalisation, the advance in technology with a development of new fabrics, the rapid progress in information technology, and the increasing demand for variety [Owen, 2001]. In particular, the sector experiences a high competition from developing countries, especially from South-East Asia [Stengg, 2001]. Spanish micro-, small- and medium-sized firms are mostly affected by the changes in the environment due to the fact that the increased competition places obviously large companies in a privileged position. As the answer to the competitive pressures, Spanish textile companies improved their competitiveness by substantially reducing mass production and concentrating instead on a wider variety of products with a higher value added. The direct results of those transformations are considerable reductions in production and employment. As a final consequence, the companies are in the process of developing the specific competitive advantages based on innovation, design, quality, creativity and use of information technologies [Stengg, 2001].

Since the early nineteenth century, the Spanish textile industry has been strongly concentrated in Catalonia, especially the leading textile activity of weaving. In 2000 there were 98 210 people employed in the Catalan textile industry, representing 35% of the whole employment in the sector. The production equalled 6176 millions of euros, which stands for the 41% of the national textile production*.

* According to the *Textile-clothing industry 2004/Spain. Practical guide*.

2. Methodology

This section explains the foundations of Data Envelopment Analysis model and its recent development in the form of bootstrapping methods. *DEA* is a nonparametric technique for identifying efficient production frontiers and evaluating the relative efficiency of decision making units (*DMUs*), each of which is responsible for converting multiple inputs into multiple outputs. As such it considers multidimensional aspects of organizational performance, which is a characteristic not available in other models such as financial ratio analysis. In ratio models, as opposed to DEA, it is difficult to gain an overall image of performance as every ratio usually indicates a different level of performance. Only if we are able to combine well several financial ratios into a summary measure of performance, they conform better to *DEA* conclusions. Hence, both techniques are usually regarded as complementing each other [Thanassoulis et al., 1996].

DEA involves the application of the linear programming techniques to given inputs consumed and outputs produced by firms. Next *DEA* constructs an efficient production frontier based on the best practices. Each firm's efficiency is then measured relative to this frontier. In recent years there has been an extensive methodological growth of the *DEA*, giving rise to the development of many different models[*]. Concerning the technology, *DEA* specifications invoke different assumptions about returns to scale. Returns to scale measure the change in output levels due to the changes in input levels. Constant returns to scale (*CRS*) imply that an increase in input levels results in a proportional increase in output levels. On the other hand, variable returns to scale (*VRS*) imply that an increase in the input levels does not necessarily result in a proportional increase in output levels, that is, the output levels can increase (increasing returns to scale) or decrease (decreasing returns to scale) by a different proportion than the input increment. The original *DEA* model proposed by Charnes et al. [1978] assumes constant returns to scale. This premise is only appropriate when all companies are operating at an optimal scale, however in practice certain constraints might cause the optimal scale to be impossible to achieve. As the answer to those problems, Banker et al. [1984] developed the *VRS* model, which permits the firms to be compared with those of similar size.

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[*] A detailed review of majority of existing models can be found in Cook and Seiford [2009].

From the efficiency measure point of view, input- and output-oriented models can be distinguished. The input-oriented model aims at minimizing inputs while maintaining outputs constant, while the output-oriented one focuses on maximization of outputs and still utilizing the input levels specified originally*. In both cases, efficiency can be considered from two perspectives: technical and scale [Dimara et al., 2003]. Technical efficiency is the distance from the point of the company current input-output combination to the production frontier under constant returns to scale. It is often referred to as global technical efficiency. On the other hand, scale efficiency shows if correct scale of inputs for the output level was chosen. We can talk also about pure technical efficiency, free of scale efficiency effects, that is calculated under variable returns to scale specification.

In this study, an input-oriented model is used due to the characteristics of the industry chosen. In order to survive, textile firms cannot assume to expand their market share in a significant way because of the increasing competition. Instead, companies change to the type of products based on intangible assets directed to niche markets, subcontract parts of the manufacturing process, reduce the size of factories as well as decrease the employment, which is a clear orientation towards the input reduction. In the input-oriented model, the efficiency score is bounded from above by 1, when the score of 1 means that the firm is efficient. The technology chosen is *VRS* because our dataset includes numeric values of various magnitudes. However, we calculate also the scores under *CRS* to be able to measure scale efficiency.

The mathematical formulation of the *VRS* input-oriented model goes as follows. Suppose we have n *DMUs* to be evaluated and each of them consumes varying amounts of m different inputs to produce s different outputs. DMU_k consumes the quantity $X_k = \{x_{ik}\}$ of inputs $i = \{1,2, \dots , m\}$ and produces the quantity $Y_k = \{y_{jk}\}$ of outputs $j = \{1,2, \dots , s\}$. The model evaluates the efficiency score of each *DMU* observed called DMU_o relative to other *DMUs*. The linear model can be described as below:

* There exists also a hyperbolic orientation which simultaneously focuses on increasing outputs and minimizing inputs.

$$
\begin{aligned}
& Min \quad \theta-\varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{j=1}^{s} s_j^+\right) \\
& subject\ to \quad \sum_{k=1}^{n} x_{ik} z_k + s_i^- = \theta x_{io}, \qquad i=\{1,2,\ldots,m\} \\
& \sum_{k=1}^{n} y_{jk} z_k - s_j^+ = y_{jo}, \qquad j=\{1,2,\ldots,s\} \\
& \sum_{k=1}^{n} z_k = 1 \\
& z_k, s_i^-, s_j^+ \geq 0
\end{aligned} \tag{1}
$$

where:

θ is the efficiency coefficient,
ε is a very small – archimedean – positive number,
x_{ik} stands for quantity of input $i = \{1,2, \ldots, m\}$ consumed by DMU_k ($k = 1, \ldots, n$),
y_{jk} stands for quantity of output $j = \{1,2, \ldots, s\}$ produced by DMU_k,
x_{io} represents quantity of input i consumed by the observed unit under analysis DMU_o,
y_{jo} represents quantity of output j produced by the observed unit under analysis DMU_o,
z_k symbolises the activity levels associated with inputs and outputs of DMU_k,
s^- is the input slack,
s^+ is the output slack.

Note that the restriction $\sum_{k=1}^{n} z_k = 1$ corresponds to the *VRS* model. The computation of efficiency scores involves solving one linear program for each *DMU*. The firm is efficient when the slacks are equal to zero.

Such formulation of *DEA* is deterministic as it does not allow for random error. In other words, *DEA* assumes that the distance between the observation and the efficient boundary reflects only inefficiency. However, it reflects both inefficiency and noise as the input-output levels could be subject to a measurement error or some input-output variables might be omitted. Hence, it would be desirable to determine the statistical properties of estimated *DEA* scores as they are essential for their interpretations and inference. Recent *DEA* literature allows for this. In particular, Simar and Wilson [1998] proposed to use bootstrapping technique to correct *DEA* estimators for a bias and to estimate the confidence intervals for those indices. Bootstrapping could be defined as a repeated simulation of the data-generating process through resampling and applying the original estimator to each simulated sample so that resulting estimates imitate the original unknown sampling distribution of the estimators of interest. To introduce the bootstrap procedure mathematically, we denote $\chi = \{(\mathbf{x}_k, \mathbf{y}_k), k = 1, \dots, n\}$ as an original sample of *n DMUs* for which bootstrap should be estimated. The algorithm can be summarized in the following steps [Simar and Wilson, 1998, 2000]:

1. The computation of the efficiency scores $\hat{\delta}_k$ for each DMUs $k = 1, \dots, n$ by solving the linear programming model described by (1).
2. Using kernel density estimation and reflection method (smooth bootstrap*), the generation of the random sample of size j from $\{\hat{\delta}_k, k = 1, \dots, n\}$, resulting in $\{\delta^*_{kb}, k = 1, \dots, n\}$.
3. The generation of the pseudo sample $\chi^* = \{(\mathbf{x}^*_k, \mathbf{y}^*_k), k = 1, \dots, j\}$ to form the reference bootstrap technology.
4. The computation of the bootstrap estimation of efficiency $\hat{\delta}^*_{kb}$ of $\hat{\delta}_k$ for each $k = 1, \dots, n$.
5. The repetition of steps 2)-4) B times in order to obtain a set of estimates $\{\hat{\delta}^*_{kb}, b = 1, \dots, B\}$.

Having the bootstrap values computed, we obtain the following measures:

a) bootstrap bias for the original estimator $\hat{\delta}_k$: $bia\hat{s}_B(\hat{\delta}_k) = B^{-1}\sum_{b=1}^{B}\hat{\delta}^*_{kb} - \hat{\delta}_k$,
b) bias-corrected estimator of δ: $\hat{\hat{\delta}}_k = \hat{\delta}_k - bia\hat{s}_B(\hat{\delta}_k) = 2\hat{\delta}_k - B^{-1}\sum_{b=1}^{B}\hat{\delta}^*_{kb}$,
c) confidence intervals for efficiency scores, which involves the following steps:
   – sort the values $(\hat{\delta}^*_{kb} - \hat{\delta}_k)$ for $b = 1, \dots, B$ and delete $(\frac{\alpha}{2} \times 100)$ – percent of the elements at either end of this sorted array,
   – set $-\hat{b}^*_\alpha$ and $-\hat{a}^*_\alpha$ $(\hat{a}^*_\alpha \le \hat{b}^*_\alpha)$, equal to the endpoints of the resulting array, then the estimated $(1-\alpha)$ – percent confidence interval is formulated as: $\hat{\delta}_k + a^*_\alpha \le \delta_k \le \hat{\delta}_k + b^*_\alpha$.

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* For details of statistical rationale see: Simar and Wilson [1998].

3. Data

The data used in this study come from the *SABI* database. *SABI* (Sistema de Análisis de Balances Ibéricos) contains financial accounts of Spanish and Portuguese companies classified according to the *NACE Rev. 1.1 code*[*]. To delimit the scope of our study we searched for micro, small and medium-sized textile companies operating in the Spanish region of Catalonia. Following the *EU* definition, the category of *SMEs* is made up of enterprises which employ fewer than 250 persons and which have an annual turnover not exceeding 50 million euros and/or an annual balance sheet total not exceeding 43 million euros[**]. Furthermore, we delimit the sample to the firms representing the leading textile activity – textile weaving[***]. After filtering out some firms that did not provide all the information necessary or with negative auditors' opinion on the data, the final sample consists of 66 firms that operated in Catalonia from 1996 to 2001.

We have some year-end variables from the balance sheet and the profit and loss account for individual firms. Although there are a number of potential problems with accounting data, the *DEA* literature using this type of information is very extensive. The studies apply a huge variety of different variables for inputs and outputs and there is no consensus which combinations are the most appropriate. Among outputs, the most frequently applied in the studies are sales revenues [Zheka, 2005; Zhang et al., 2001]. Sometimes this variable is used in conjunction with others, such as profit before tax [Worthington, 1998; Zhu, 1996]. However, it is believed that profits are not a good approximation of outputs, because they can be strongly influenced by the environmental conditions [Al-Shammari, 1999]. With regard to input variables, Hill and Kalirajan [1993] for example work with three inputs: cost of employees, material cost and value of investments, while Thore et al. [1994] use operating cost, fixed assets and number of employees. Basing on those studies and given the limitation of available data, in this paper we consider the production

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[*] *NACE Rev. 1.1* is a classification of economic activities used by *EUROSTAT* and published in 2002. It is an extension of *ISIC Rev. 3* activity representation created by the United Nations. According to this classification number 17 represents Manufacture of textiles.

[**] Within this category, small firms are those that employ fewer than 50 persons and whose annual turnover or annual balance sheet total does not exceed 10 million euro, while micro companies employ less than 10 persons and have annual turnover or annual balance sheet total that does not exceed 2 million euro.

[***] Textile weaving includes cotton-type, woollen-type and worsted-type weaving. It is represented in *NACE Rev. 1.1* classification by the number 172.

of woven textiles as the outcome of labour, fixed assets and variable inputs [materials]. The production is estimated via sales revenues. Hence, we apply the following variables*:

Inputs	***Output***
a. Number of employees	a. Sales revenues
b. Fixed assets	
c. Material expenses	

The basic descriptive statistics of these data are presented in Table 2.

Table 2

Input/output specification for *DEA* (descriptive statistics for 1996-2001)

Variable	Mean	Std. Dev.	Min	Max
Output				
Sales revenues	2778.705	4024.828	93	23502
Input				
Number of employees	23	19.458	1	114
Fixed assets	459.879	978.957	0	11822
Material expenses	1862.152	3313.954	1	19872

Note:
All variables, except for number of employees, are expressed in thousands of euros.

We can observe that the mean textile company in our sample has 23 employees and almost 3 million of sales revenues. Hence, it belongs to the category of small companies. In addition, our average sample firm represents well the European population as the mean textile company in Europe has 19 employees [Stengg, 2001].

4. Results

The bootstrap algorithm of Simar and Wilson [1998, 2000] described before in this paper was applied with *FEAR 1.1 package*** with $B = 2000$

* We checked the correlations among inputs and outputs and we did not find any high correlation between inputs neither a very low correlation between inputs and outputs, which reasonably validates our DEA model (no input could be excluded and all variables fit the model).

** *FEAR* is a software package for frontier efficiency analysis with *R*, which allows computing many different estimates of efficiency. The software is freely available from: http://www.clemson.edu/economics/faculty/wilson/Software/FEAR/fear.html.

bootstrap replications. Table 3 summarizes the means of the following measures: efficiency scores, bias-corrected efficiency scores and confidence intervals for true efficiency scores in *VRS* specification.

Table 3

Mean *DEA* efficiency scores under *VRS*

Years	Efficiency score	% of efficient firms	Bias-corrected efficiency score	Confidence interval	
				Lower bound	Upper bound
1996	0.876 (0.136)	34.848	0.807 (0.113)	0.732 (0.097)	0.871 (0.135)
1997	0.877 (0.130)	33.333	0.814 (0.109)	0.738 (0.095)	0.873 (0.130)
1998	0.880 (0.141)	40.909	0.810 (0.121)	0.730 (0.110)	0.875 (0.140)
1999	0.888 (0.128)	37.878	0.829 (0.109)	0.751 (0.103)	0.884 (0.128)
2000	0.896 (0.116)	36.364	0.837 (0.097)	0.757 (0.085)	0.892 (0.116)
2001	0.872 (0.128)	34.848	0.806 (0.105)	0.729 (0.090)	0.868 (0.128)
1996-2001	0.881 (0.130)	36.364	0.817 (0.109)	0.740 (0.097)	0.877 (0.129)

Note:
The values presented in the brackets show the standard deviations.

The first thing to note in Table 3 is that during the period under investigation textile firms in our sample, on average, have the relatively high levels of efficiency of 0.881 with standard deviation of 13%. The number of firms that are classified as relatively efficient is rather high in individual years (more than 30%). When taking bias-corrected estimates, mean efficiency in the sample decreases to 0.817 with standard deviation of 10.9%. This value indicates that there is still a room for efficiency improvement for firms by reducing the input. In particular, to be efficient the companies should be able to obtain the same sales revenues by reducing the consumption of production resources (employees, fixed assets and material costs) at least in 18.3%. Furthermore, Table 3 reveals a slight increase in the original efficiency scores up to the year 2001 when the efficiency dropped. To sum up: on average, the bias-corrected efficiency scores are lower than the original ones (indicating higher level of inefficiency) and the values of real efficiency scores are contained in the interval between 0.740 and 0.877 as indicated by confidence intervals.

We further applied *DEA* with bootstrap in *CRS* specification. If there is a difference in the *CRS* and *VRS* scores, it indicates that the company is suffering from scale inefficiency. The scores for scale efficiency can be computed by dividing the efficiency scores in *CRS* by the efficiency scores in *VRS*. Obviously, if scale efficiency score is equal to 1, it means that *CRS* efficiency is equal to *VRS* efficiency and the firm is said to be scale efficient. Otherwise, the firm is scale inefficient. The Table below summarizes the decomposition of bias-corrected efficiency scores computed under *CRS* (global technical efficiency) into *VRS* bias-corrected efficiency scores (pure technical efficiency) and scale bias-corrected efficiency scores during the period 1996-2001 (yearly average).

Table 4

Global bias-corrected technical efficiency decomposition

Years	*CRS* bias-corrected efficiency scores	*VRS* bias-corrected efficiency scores	Scale bias-corrected efficiency scores
1996	0.773 (0.123)	0.807 (0.113)	0.959 (0.080)
1997	0.754 (0.138)	0.814 (0.109)	0.927 (0.115)
1998	0.740 (0.147)	0.810 (0.121)	0.914 (0.116)
1999	0.801 (0.124)	0.829 (0.109)	0.966 (0.075)
2000	0.798 (0.115)	0.837 (0.097)	0.953 (0.074)
2001	0.762 (0.124)	0.806 (0.105)	0.945 (0.083)
1996-2001	**0.772 (0.130)**	**0.817 (0.109)**	**0.944 (0.094)**

Note:
The values presented in the brackets show the standard deviations.

Table 4 reveals a slight decrease in the level of global efficiency until 1998, which was largely due to a dramatic reduction in scale efficiency. Global efficiency decreased from a mean value of 0.773 in 1996 to 0.740 in 1998, which reflects an increase in the distances separating the best practices from the rest of textile firms in the sample. Scale efficiency decreased from a value of 0.959 in 1996 to 0.914 in 1998, hence the companies were positioned farther from the optimal scale. This effect was partially offset by the moderate improvement in pure efficiency in 1997. In 1999 overall efficiency increased due to the increment in pure efficiency and scale efficiency, while it continued to drop until 2001 as a result of a substantial drop in scale efficiency in spite of an increase in pure efficiency. In addition, it is worth observing that despite an almost continuous decrease, the mean scores of scale efficiency are still relatively high: ranging from 0.966 to 0.914.

Furthermore, we perform a test of stochastic dominance to evaluate if distributions of bias-corrected efficiency scores of micro companies are different to those of small and medium-sized. Stochastic dominance refers to the differences that may exist between two distributions, characterized by their cumulative distribution functions[*]. Formally, let us suppose that we have two distributions *A* and *B* with cumulative distribution functions *F* and *G*, respectively. First order stochastic dominance of *A* relative to *B* is defined by: $F(x) - G(x) \leq 0$ for any argument $x \in R$ [Delgado et al., 2002]. We need to test the following hypothesis: $H_0 : F(x) = G(x)$ *for all* $x \in R$ versus $H_1 : F(x) \neq G(x)$ *for at least one value of* x. To test this hypothesis the Kolmogorov-Smirnov two-sided test is used [Conover, 1971]. Because the application of this test requires independence of observations and as we possess data of six years, we calculate it separately for each time period. Table 5 presents the mean values of bias-corrected efficiency scores under *VRS* and the P-values of Kolmogorov-Smirnov test.

Table 5

Micro versus small and medium-sized firms

DMU	1996	1997	1998	1999	2000	2001	Mean 1996-2001
Micro	0.856	0.866	0.849	0.866	0.863	0.847	0.858
Small- and medium-sized	0.789	0.794	0.795	0.815	0.828	0.791	0.802
P-value	0.011	0.003	0.138	0.007	0.579	0.085	0.000

The results of the tests suggest that the null hypothesis of equality between distributions of micro firms and small and medium-sized can be rejected in all years analyzed, except for 1998 and 2000. As the mean values of bias-corrected efficiency are higher for micro firms, micro companies statistically dominate small- and medium-sized ones in all years, except for 1998 and 2000. In addition, Figure 1 reports the differences between the bias-corrected efficiency scores distributions for those types of companies. It can be seen on the graphs that the position of the distribution for micro companies with respect to small- and medium-sized ones indicates higher levels of efficiency for micro firms for all years. However, the distributions in 2000 lie very close one to another, which can further confirm the insignificance of P-value results for this year.

[*] Test of stochastic dominance is more general than the Wilcoxon test as it tests if the entire distribution is different.

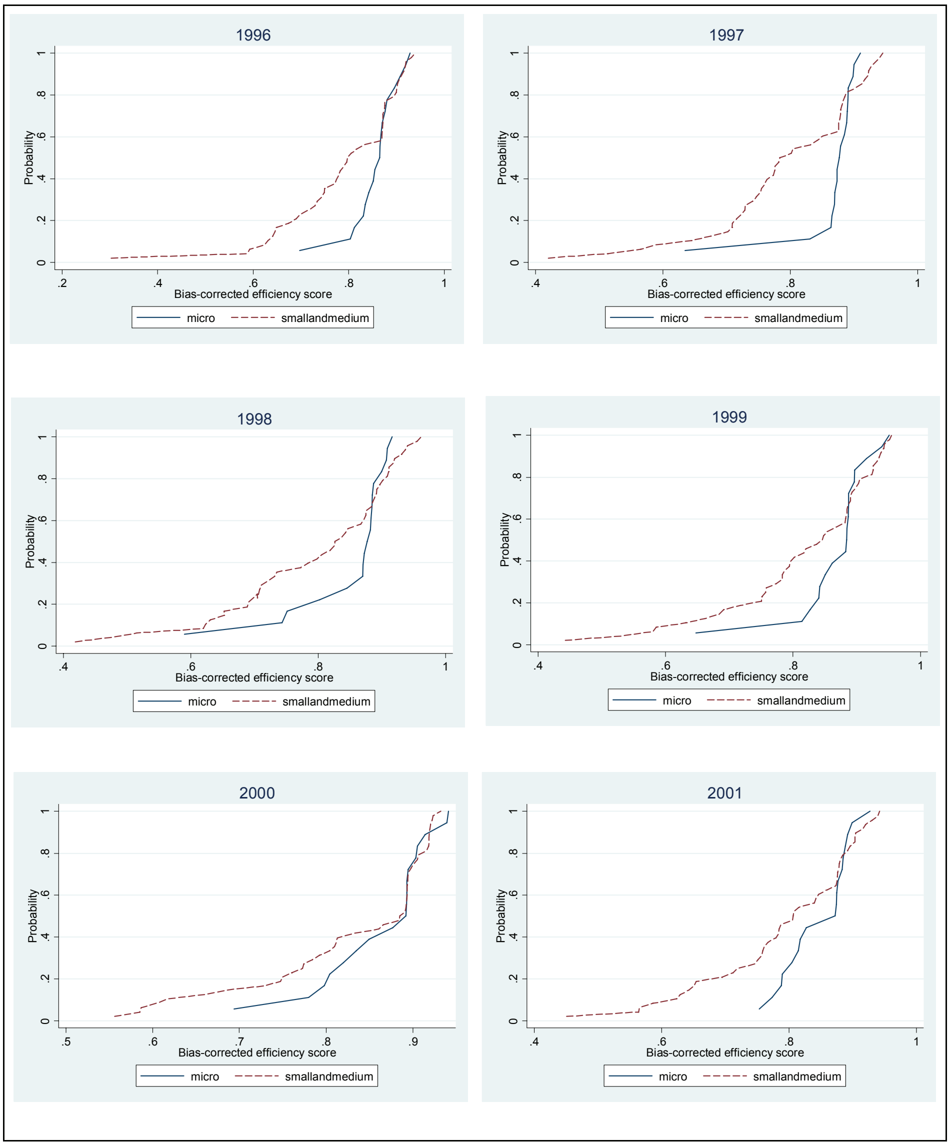

Figure 1. Differences in bias-corrected efficiency scores: micro- versus small- and medium-sized firms (smooth sample distribution function)

Conclusions

This paper aimed at assessing the efficiency of micro-, small- and medium-sized firms in the textile industry in Catalonia during the second half of the 1990s and the beginning of 2000. In the empirical analyses we applied an input-oriented *DEA* model and we used the bootstrap method to give the statistical significance to indices computed. The results have shown that textile firms in our sample are on average relatively highly efficient in their productive process as efficiency score reached the value of 0.881 or 0.817 when the bias-corrected score was taken into account. The efficiency indices fluctuated only slightly, hence the effect of increased competition in the sector cannot be observed by augmented efficiencies. Probably, firms focused mainly on the investment in technological development. In addition, when performing the test of stochastic dominance we found that micro companies are more efficient than small- and medium-sized ones in all years, except for 1998 and 2000. The conclusions from the inefficiencies observed in the sample are the following. First of all, there is room to decrease input for textile firms. In order to improve efficiency companies should be able to obtain the same output as reflected by the sales revenues by reducing the production resources of employees, fixed assets and material costs. Secondly, the firms in the sample experience some small problems with scale efficiency by choosing an incorrect scale of inputs for output level.

The empirical study presented here has some limitations, which open the areas for future research. In particular, efficiency indices computed do not separate the effect of firms moving towards the benchmark frontier from the effect of the movements of the frontier across time (technological development). To separate both moves, in the future research the Malmquist index must be used, also to analyze more precisely the impact of increased competition in the textile sector. Moreover, in the future research, the *DEA* approach could be compared with financial ratio analysis to find out, for example, if and to what extent the two models agree or disagree on the performance of firms.

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