sustainability

MDPI

Article

Application of the DEA Double Bootstrap to Analyze Efficiency in Galician Sheltered Workshops

María-Celia López-Penabad *, José Manuel Maside-Sanfiz, Juan Torrelles Manent and Ana Iglesias-Casal

Faculty of Economics and Business, University of Santiago de Compostela, 15782 Santiago de Compostela, Spain; josemanuel.maside@usc.es (J.M.M.-S.); juan.torrelles@rai.usc.es (J.T.M.); ana.iglesias.casal@usc.es (A.I.-C.)

* Correspondence: celia.lopez@usc.es; Tel.: +34-8818-11626

Received: 28 June 2020; Accepted: 11 August 2020; Published: 16 August 2020

Abstract: Sheltered workshops (SW), as social enterprises, need to be efficient and maintain a balance between social aspects and economic prosperity. An important part of research on the subject has been focused on measuring the economic value created by these entities. In this study, we analyzed performance of SWs in Galicia (Spain), from the point of view of efficiency, combining social and economic aspects and investigating its key determinants. Using panel data from 609 entities from 2008 to 2017, we followed Simar and Wilson's two-stage approach (2007). Specifically, we used data envelopment analysis (DEA) at the first stage to estimate efficiency scores and then used truncated regression estimation with double-bootstrap to test the significance of explanatory variables. Our results show that SWs have high levels of performance, higher in economic than in social terms, and we found that several factors, such as size and age, positively influence total, economic and social efficiency individually. We also found a positive, significant relationship between social efficiency and economic profitability.

Keywords: social enterprises; sheltered workshops; performance evaluation; data envelopment analysis; efficiency determinants; two-stage bootstrap Simar and Wilson procedure

1. Introduction

While work is a basic right for disabled people, the figures highlight the problems of labor insertion and marginalization they face. Disabled people are a large and low labor participation group in Spain, with activity and employment rates well below the nondisabled population and, once they enter the labor market, nondisabled workers exceed the able Spanish unemployment rate by 10 points [1].

Incapacitated individuals can exercise their right to work through ordinary employment (enterprises and public administrations, etc.), protected employment, and self-employment. Within protected employment, the sheltered workshop (SW) is the most widely used initiative.

In recent years, there has been an increase in contracts for the disabled people in Spain, this increase is mainly linked to the SW contracts to the detriment of ordinary companies. The percentage of SW contracts compared to the total number of contracts for disabled people in Spain rose from 53.31% in 2008 to 71% in 2018.

SWs are part of social economy companies, their main objective being to generate social value, providing paid work and support that allows disabled people to learn and train for jobs that will enable them to be integrated into the ordinary labor market. In order to carry out their mission, they develop economic activities that are an important financial resource to support their social mission.

Therefore, SWs respond from a legal and academic point of view to the concept of social enterprise (SE) and there is broad international consensus to identify SWs as SEs [2].

While more and more actors are interested in how SEs need to be governed to achieve their dual, social and financial, goals, academic work addressing these issues is still scarce. There is a lack of research on how this combined value is generated, how it is measured, and how it can be transmitted to different stakeholders. Social value is an abstract and difficult concept to measure, and efficiency is one of the measures that can be used to analyze whether it is possible to achieve the sustainability goal. A debate is currently open about how these organizations should be evaluated.

Government support for SWs depends on the economic situation individual countries are experiencing. The decrease in the provision of social programs in times of crisis usually leads to a reduction in subsidies received by SWs and requires greater professionalization, a consequence of the higher requirements imposed by the public administration to access its aid. In this context, it is necessary to carry out an assessment of the effects of these changes and to determine whether SW models are sustainable, even including adverse crises and/or scenarios of decreased aid and subsidies.

As SEs, and SWs particularly, are considered a relatively new field in academic research, previous studies evaluating social and financial efficiency separately using a double bottom line approach are scarce. We do not know of any relating to SWs in Spain, nor do we know of the existence of studies that separately evaluate the performance of SWs by differentiating profit and nonprofit entities, nor are we aware of studies that analyze the influence of external factors on the efficiency of these types of entities, calculated by applying DEA (data envelopment analysis) methodology.

The objective of this work was to analyze the efficiency of the SWs existing in Galicia, differentiating between profit and nonprofit entities, and determine which exogenous factors influence said efficiency.

As the main contributions of our work, we can highlight the following. First, it adds empirical evidence to assess the efficiency of SWs using both operational and social indicators. This will highlight the value created and allow their own managers, public administrations, and other stakeholders, to evaluate and understand their performance. To do this, we used the DEA technique, which also allowed us to analyze the extent to which the mission of SWs is fulfilled over time. Secondly, this work covers a broad time horizon, we explored efficiency during the years of the most recent crisis in Spain (2008–2013) and the subsequent period of economic recovery (2014–2017). It seems appropriate to provide evidence to enable a new stage of strong economic and social instability to be addressed, which we are currently experiencing. Thirdly, this work analyzed the determinants of the technical efficiency of SWs. There are hardly any previous studies in this regard, we do not know any the Spanish case and the identification of the factors that affect their efficiency is a fundamental task to improve their management and help them survive in the current environment. At the methodological level, we used the two-stage double bootstrap DEA approach, Algorithm II proposed by Simar and Wilson [3] making for more robust and reliable results than the techniques traditionally used in this line of research.

The rest of the paper is structured as follows: Section 2 presents a review of empirical work related to the measurement and analysis of efficiency in different SEs, and the hypothesis. Section 3 sets out the methodology used in the study and defines the sample and variables. The main results are set out in Section 4. Finally, Section 5 sets out the conclusions and limitations of this work.

2. Literature Review. Performance Evaluation: An Overview

Research related to the analysis of technical efficiency has developed significantly, resulting from a highly competitive business environment that requires a more rational use of resources. However, there are few papers that analyze efficiency for SWs or similar SEs, although most concluded that these companies generate both social and economic value and that there is a relationship of dependence between them.

In this sense, the work of Battilana et al. [4] stands out. It analyzed the factors that influence the social performance of panel data of French WISEs (work integration social enterprises). These are similar companies to SWs, as they provide their beneficiaries with work training and individualized social advice. The results of the regressions made by these authors show that social imprinting and economic productivity are positively associated with social performance. However, social imprinting is negatively related to economic productivity, and, as a result, has an indirect negative impact on social performance.

Bellostas et al. [2], in a sample of Spanish SWs, pointed out that these play a dual role in society and that they generate both economic and social value, highlighting the existence of a strong relationship of dependence between them. However, they indicated that it is necessary to prioritize the maximization of social value or economic value, believing that it is not possible to combine them both. The social component is the main one, and although the total value created would include the economic variable, it is not possible to speak of shared value, the economic value is a consequence of the social strategy implemented by the SW management.

Efficiency is one of the measures that can be used to analyze whether it is possible to achieve the sustainability objective in this type of entity. Some works analyze value creation by applying this concept using the DEA methodology. Dia and Bozec [5] pointed out that DEA can be used to assess the performance of SEs, although, surprisingly, not very often, despite its great analytical capacity and adaptability to different formats and organizational contexts.

Lee and Seo [6] studied the job-creation type of SEs for vulnerable social groups in Korea. They focused on the type of employment created by the SEs and for this they used a DEA model that looked at both economic and social aspects. They used labor costs and assets as inputs, and, as economic outputs, revenue and operating profit and, as social outputs, the rate of vulnerable employees and the percentage of reinvestment of the result for social purposes. In addition, they incorporated grants into the model as a factor that can play a dual role, as financial resources (inputs) or as a measure of output (social value creation). They concluded that grants play a different role in assessing the performance of SEs according to their age. Older companies run their businesses trying to reduce them, whereas younger ones increase them.

Staessens et al. [7] performed a longitudinal DEA analysis on a Flemish SW sample. They used fixed tangible assets, the maximum annual number of subsidized employment places, and the operating costs as inputs. As for outputs, they differed between economic (measured through revenue) and social (number of disadvantaged employees), pointing out their dual role. More efficient SWs have a stronger economic orientation and place a greater emphasis on business activities, while achieving higher social performance. On the contrary, in less efficient SWs, a reverse mission drift is observed, they pay excessive attention to social objectives at the expense of economic ones. There is a decrease in their economic efficiency that was not compensated by an increase in social efficiency, which causes a fall in overall efficiency. Organizations that maximize economic performance are not only more economically efficient but also socially efficient and tend to achieve greater overall efficiency (sustainability) in the long term. The relationship between the social and economic variable is bidirectional, different from that pointed out by Bellostas et al. [2].

From a methodological point of view, two orientations are distinguished in performance literature: (i) parametric analyses and (ii) nonparametric analyses. The pros and cons of both approaches have been widely discussed (among others, [8,9]).

One of the advantages of parametric approximations is that they not only measure efficiency, but also incorporate into one model the determinants of efficiency, that is, the explanatory variables of that efficiency. Nonparametric approximations estimate the production frontier and measure the distance to this frontier with input/output combinations. Identifying the determinants of efficiency is of great relevance for this reason and in the field of nonparametric efficiency analysis there are frequent approximations that combine DEA with a regression analysis that uses DEA estimates as a dependent variable.

Simar and Wilson [3] mentioned numerous publications that employed two-stage procedures. In these early two-stage applications, the second stage is typically a censored regression (Tobit) to analyze the nature of efficiency DEA scores, or simply an ordinary least squares (OLS) regression. These authors developed a two-stage procedure that, as the main difference from the previous approximations, applies a truncated regression model, using a parametric bootstrap procedure that is consistent with the underlying data-generating process and estimates the regression raised. The procedure provides estimated standard errors and confidence intervals that do not suffer from bias due to the correlation of estimated efficiency scores, thus overcoming some difficulties arising from the DEA methodology. DEA depends on the quality of the data used, is very sensitive to sampling bias, error measurement and outliers. Generating skewed results and overestimated efficiency scores [10,11].

Banker and Natarajan [12] proposed a coherent statistical model in which a second-stage regression is meaningful. The second-stage regression equation is log-linear, and OLS method provides consistent estimation. Banker and Natarajan [12] (p. 56) stated: "Specifically, we prove that when data are generated by a monotone increasing and concave production function separable from a parametric function of the contextual variables, a two-stage approach comprising a DEA model followed by and ordinary least squares (or ML) model yields consistent estimators of the impact of the contextual variables".

Simar and Wilson [13] stated that in literature, only two statistical models have been proposed in which second-stage regressions are well-defined and meaningful. In the model considered by Simar and Wilson [3], truncated regression provides consistent estimation in the second stage, whereas in the model proposed by Banker and Natarajan [12], OLS provides consistent estimation.

Recently, many papers have used a two-stage DEA methodology to analyze efficiency across different types of organizations, but few have been applied to SEs and we do not know of any for SWs. We will now consider these works.

Martínez Franco and Guzmán Raja [14] applied a logit regression model to a sample of state care foundations. By applying the DEA, they determined the border of 'best practices' of the evaluated units. The study was complemented by a two-stage DEA analysis to evaluate the possible association of relevant variables in the foundation sector with the performance of these organizations previously calculated. The variable long-term debt level increased their efficiency, while size and age decreased it. The liquidity variable had no statistical significance.

Solana, et al. [15] analyzed the determinants of efficiency in Spanish foundations. They used the DEA methodology and the parametric double bootstrap Simar and Wilson model. Endowment, total assets, total expenditure, and the number of employees were used as inputs. The outputs considered were the level of income obtained and the number of users attended. They concluded that the most efficient foundations are characterized by their private nature, have more seniority, have volunteers, and have many patrons.

Martínez-Campillo and Fernández-Santos [16] examined the levels of financial and social efficiency in Spanish credit unions, as well as their main determinants, applying the two-stage double bootstrap DEA methodology based on panel data. They found that financial and social efficiency achieved an acceptable level—merger and acquisition activity and age were positively influential on the financial efficiency of credit unions but had a significant negative effect on their social efficiency. Regional location of such entities and the financial crisis were also crucial determinants of both type of efficiency.

Finally, Salas-Velasco [17] identified the environmental factors that explain differences in efficiency of Spanish universities using a nonparametric approach and a bootstrapped-truncated regression—a higher percentage of academics with tenure enhances productive efficiency and a higher percentage of grantees and outgoing students tend to be less inefficient.

Hypothesis

Based on the review of existing literature related to business efficiency, we raised a series of hypotheses for the second stage of our analysis, which we set out below and contrast in the results section.

Hypothesis 1. *size and efficiency. The size of an entity is measured by the volume of assets, turnover, or number of workers. We took, as a measure of the size, the total assets, considering as the first hypothesis that* *size positively influences the efficiency of SWs. We expected a positive relationship as we considered that the efficiency achieved with the available organizational resources improves with the size of the SW* [14,18,19].

Hypothesis 2. *age and efficiency. As time goes on, organizations accumulate experience and prestige; any human activity is the subject of a learning process. Therefore, our second hypothesis was that as the entity matures, it increases efficiency in achieving its objectives (in this sense,* [15,19]*). However, Martínez Franco and Guzmán Raja* [14] *concluded otherwise-younger entities are more efficient. Battilana et al.* [4] *found that the size and age characteristics explain productivity differences among WISEs but do not explain differences in social performance. Economic productivity tends to be higher in the most experienced and smaller WISEs.*

Hypothesis 3. *liquidity and efficiency. Another factor that can affect efficiency is the financial situation. Liquidity ratio, current assets to current liabilities, enables measuring the ability of the entity to cancel its debts and, therefore, hypothesis three implied a positive relationship between this ratio and efficiency. However, Martínez Franco and Guzmán Raja* [14] *did not find a significant relationship for the liquidity ratio.*

Hypothesis 4. *long-term debt and efficiency. The long-term debt ratio is the ratio of long-term liabilities to total liabilities. As a fourth hypothesis, we expected a positive relationship between long-term indebtedness and efficiency. We understand that long-term debt is associated with greater patrimonial stability, as did Martínez Franco and Guzmán Raja* [14].

Hypothesis 5. *ROA (return on assets) and efficiency. All entities, and of course SWs, need to be profitable to be sustainable. Economic aspects are a prerequisite for being able to fulfil their social mission in a sustainable way by freeing up resources for it* [2,4,6,7,20]*. Therefore, Hypothesis 5 was that there is a positive relationship between ROA and social efficiency.*

Hypothesis 6. *nature of SWs and efficiency. Practically all SWs in Galicia operate as private entities, under a for-profit legal (FPL) or a not-for-profit legal status (NPL).*

We believe that FPL SWs could be more economically efficient than NPL SWs. Although the social purpose is the same for all SWs, this is a priority in NPL SWs. Their returns on assets and equity are lower than those of FPLs, being an indicator that economic performance is not an objective in itself, but contingent on the social purpose [21,22].

We have not found any work that considers the public or private nature of SWs as a determinant of their efficiency. There are previous studies which somehow dealt with contrasting whether private organizations are more or less efficient than organizations of another kind. Thus, and related to the sector of the social economy, Guzmán et al. [23] showed that the efficiency levels of cooperative societies are lower than those presented by labor societies. Solana et al. [15] pointed out that private foundations are more efficient.

Battilana et al. [4] defined social imprinting as the foundation team's emphasis on achieving the organization's social mission. They pointed out that for WISEs, NPL status does not have a significant effect on social performance and economic productivity tends to be lower in NPL WISEs. Smith and Lewis [24] and Jay [25] pointed to the existence of a paradox inherent in the social imprinting of SEs. Although social imprinting directly boosts social performance, social imprinting indirectly weakens social performance by reducing economic productivity. Gutierrez et al. [26] pointed out that NGOs are more socially efficient than microfinance institutions operating under other organizational structures. NGOs emphasize their social role in their financial performance, although without neglecting financial efficiency and, therefore, as a result of their emphasis on social objectives, NGOs are more socially efficient than non-NGOs.

For all these arguments, some in favor of the NPLs and others of the FPLs, as hypothesis 6 we considered that there is a relationship between the nature of the SWs and efficiency, but we could not foretell if it will be positive or negative.

Hypothesis 7. *corporate group membership and efficiency. Membership in a group can increase an entity's potential because the group typically has a collaborative and supportive purpose. In contrast, there can also be a reduction in efficiency if the structure or organization is complex. According to Worthington* [27] *and Glass et al.* [28] *evidence shows that being a member of a group has a positive and significant effect on efficiency for credit unions; according to Martínez-Campillo et al.* [29] *it is not financially significant, but is significant and positive, for social efficiency. SWs are often configured as foundations, associations, or confederations, and their link to their nonprofit promoters with those who share capital, administrative tasks, and management tools is very important. Bellostas et al.* [2] *verified that entities belonging to collaborative networks show much higher levels in terms of average economic value but without significant influence on variables related to social value. Consequently, for Hypothesis 7 we considered that there is a positive relationship between membership of a corporate group and efficiency.*

Hypothesis 8. *presence of women on board of directors and efficiency. Nielsen and Huse* [30] *stated that the presence of women on corporate boards reduces the level of conflict and ensures quality in board development activities increasing its effectiveness. Ebrahim et al.* [31] *showed that aspects of corporate governance, such as the presence of women in the board composition, can be an important factor in the efficiency of SEs. As Hypothesis 8, we considered that the presence of women on the board of directors increases the efficiency of SWs.*

3. Material and Methods

3.1. Methodology

As mentioned above, there are a numerous techniques that have emerged, both parametric and nonparametric, in the operational research dealing with the measurement of efficiency. Among the nonparametric techniques used to estimate production frontiers and evaluate efficiency is the data envelopment analysis (DEA), which objectifies the results of an entity by measuring them in relation to the best results achieved by the rest.

DEA was developed for the manufacture of physical goods, where the inputs are those of the production process and the outputs are the units produced or the services provided. If we are talking about SEs, what the "alternative" production process seeks is the conversion of economic results into social achievements. Although many SEs do not seek optimization of this transformation process as their main objective, it allows the analysis of this process in terms of efficiency [32].

We applied a semiparametric two-stage double bootstrap DEA approach, specifically, Algorithm II developed by Simar and Wilson [3]. In the first stage, both efficiency scores and confidence intervals were calculated combining the classic DEA model with the bootstrap procedure. In the second stage, efficiency estimates were regressed on a set of environmental variables using the truncated regression with bootstrap.

First stage: DEA efficiency scores

DEA estimates the production frontier by using linear programming techniques that calculate the efficiency score of a DMU (decision-making unit) with respect to homogeneous entities.

Our study focused on the Galician SWs, a homogeneous population of SEs that present similar characteristics and belong to one production frontier: (i) common social mission (employing people with disabilities), (ii) similar activities (the vast majority belong to the services sector and carry out activities with few qualifications and low added value), (iii) similar regulatory environment, and (iv) similar legal form.

There are many DEA models proposed in literature (static, dynamic, with different returns to scale and orientation), also varied inputs and outputs proposed for analysis in the first stage and exogenous variables to be included in the second stage, however there is no guide to choose the model and the appropriate variables in each stage [33].

We used the CCR (Charnes, Cooper and Rhode) ([34] and BCC (Banker, Charnes and Cooper) [35] models. Both are based on radial efficiency measurements, and can be carried out from both orientations (either input or output). The CCR uses constant returns to scale and the BCC variables. The latter assumes that the evaluated entity may be operating under the variable returns to scale hypothesis, implying that the relative efficiency of each DMU is obtained by comparing that DMU with those that have produced efficient results possess similar operational dimensions.

We considered the output orientation, since economic units usually aim to maximize profits with an adequate combination of productive factors (inputs). The output approach from the point of view of SWs is also more appropriate.

The DEA, being a nonparametric method, does not require prior knowledge of the production function, supports production units with multiple inputs and outputs, does not depend on parameters that determine a priori the relationship between the two, and the data are known for certain. The linear programming problem must be solved for each of the SWs.

The closer to unity, the more efficient a company is, and the most efficient SWs would be on the border. Inefficiency is measured by the distance between the SW and the efficient border.

For each period t ($t = 1, \ldots, T$), we considered a group of n DMUs ($i = 1, 2, \ldots, n$), for which we considered a set of q outputs ($r = 1, 2, \ldots, q$) that produce $Y_{it} = \{y_{rit}\}$ and p inputs ($j = 1, 2, \ldots, p$) that consume $X_{it} = \{x_{jit}\}$.

The mathematical formulation of the CCR output-oriented model for estimating the efficiency of a decision-making unit 0 (DMU 0) is as follows:

$$Max \varnothing_{0t} \tag{1}$$

$$s.t.: \sum_{i=1}^{n_t} \lambda_{it} x_{jit} \leq x_{j0t} \qquad j = 1, \ldots, p \tag{2}$$

$$\sum_{i=1}^{n_t} \lambda_{it} y_{jit} \geq \varnothing_{0t} y_{r0t} \quad r = 1, \ldots, q \tag{3}$$

$$\lambda_{it} \geq 0 \quad i = 1, \ldots, n_t \tag{4}$$

where ϕ is the efficiency score and λ is the weight.

Since the CCR model considers the hypothesis of constant returns to scale, and in order to avoid the difficulties associated with measuring efficiency in units biased by scale inefficiencies, Banker, Charnes, and Cooper [35] proposed an alternative model (BCC model), which assumes the variable returns to scale hypothesis by adding the constraint

$$\sum_{i=1}^{n_t} \lambda_{it} = 1 \tag{5}$$

to the CCR model, which calculates pure technical efficiency (ETP) scores that take into account the scale of operations of efficient companies with respect to the DMU evaluated in each case.

In the practical application, we used a windows analysis, proposed by Charnes et al. [36], because the empirical study was carried out on panel data, comparing each DMU with itself in different periods of time. We set window width to 1 year, so this was equivalent to dividing the panel data into many datasets (each dataset contains one year's data) and analyzing each dataset one by one.

DEA offers several advantages when examining the performance of SWs. In the context of SWs, social and economic indicators are expressed in different measurement units, both nonfinancial and financial. For instance, the number of disadvantaged employees for SWs expresses their social performance, while their economic performance is expressed using monetized financial accounting variables. Measuring economic and social performance together can cause aggregation problems related to weightings given to both aspects, and standardization problems, when handling different objectives with different units of measurement [7].

DEA can be particularly useful in these cases since it does not require prior judgment on weighting granted to social and economic aspects, DEA is characterized by benefit of the doubt, which allows specifying weightings endogenously. Furthermore, it is invariant to measurement units for both input and outputs and it facilitates the usage of these important measures in a unified performance index.

DEA, in addition to efficiency indicators, will provide information to improve management of the inefficiency of the DMUs (reduce inputs, increase outputs), to identify the set of efficient SWs and the slack variables. This information will allow us to advise actions to increase efficiency and be more competitive from an economic–financial and social point of view.

DEA methodology also has different limitations. The most important is that it tends to generate biased estimates. In order to correct the problems associated with the sampling noise in the resulting efficiency DEA estimators, and within the first stage initiated with the DEA, we used the procedure proposed by Simar and Wilson [37] for bootstrapping the initial efficiency scores and obtaining bias-corrected efficiency estimations $\hat{\hat{\varnothing}}_{it}$.

Second stage: Truncated Regression

Next, we applied the Simar and Wilson [3] truncated regression model, Algorithm II, developed to determine the explanatory character that certain exogenous variables have over efficiency levels. The basic idea of the analysis of this second stage is based on the idea that the efficiency levels of the SWs analyzed depend on a number of environmental factors that are basically not controllable by these.

The second stage regression is given by:

$$\widehat{\widehat{\varnothing}}_{it} = \beta Z_{it} + \delta D_t + \varepsilon_{it} \qquad i = 1, 2, \ldots, n_t \qquad t = 1, \ldots, T \tag{6}$$

where $\widehat{\widehat{\varnothing}}_{it}$ is the dependent variable, the bootstrapped bias-corrected efficiency score for $\mathrm{DMU_i}$ for each year t; Z_{it} is a vector of environmental variables which is expected to explain the efficiency variations; D_t is a vector of year dummies (from 2009 to 2017, with 2008 being the reference year); β and δ are the parameters to be estimated in the second stage that establishes the relationship between independent variables and efficiency and the annual effects on efficiency, respectively; ε_{it} is an independent error term that follows the normal distribution with a zero mean and σ_ε^2 variance $N\left(0, \sigma_\varepsilon^2\right)$ with left-tail truncation $(1 - \hat{\beta}\mathrm{Z_{it}} - \hat{\delta}D_t)$.

Algorithm II by Simar and Wilson [3] has been applied to the estimation of the regression model using the double bootstrap procedure. The steps of the algorithm are presented below:

1. For each period $t = 1, \ldots, T$, we used the estimated efficiency score for each SW and year t $\left(\hat{\phi}_{it}\right)$.
2. We used the method of maximum likelihood to obtain an estimate $\hat{\beta}$ of β and $\hat{\delta}$ of δ, as well as $\hat{\sigma}_\varepsilon$ of σ_ε in the truncated regression of $\left(\hat{\phi}_{it}\right)$ on (Z_{it}) and (D_t).
3. For each $(i = 1, \ldots, n_t)$ and $(t = 1, \ldots, T)$, we replicated the followings steps B_1 times, to obtain B_1 bootstrap estimates $\left\{(\hat{\phi}_{it}^{b})\ b = 1, \ldots, B_1\right\}$
   a. Generate the residual $\widetilde{\varepsilon}_{it}$ from the normal distribution N(0, $\hat{\sigma}_\varepsilon^2$) left-truncation $\left(1 - \hat{\beta}Z_{it} - \hat{\delta}D_t\right)$.
   b. Estimate $\widetilde{\phi}_{it} = \hat{\beta}Z_{it} + \hat{\delta}D_t + \widetilde{\varepsilon}_{it}$
   c. Produce a pseudo-dataset $(\widetilde{x}_i, \widetilde{y}_i)$, where $\widetilde{x}_i = x_i$ and $\widetilde{y}_i = (\hat{\phi}_{it}/\widetilde{\phi}_{it})y_i$
   d. Use the pseudo-dataset $(\widetilde{x}_i, \widetilde{y}_i)$ to estimate the pseudo efficiency score DEA $(\hat{\phi}_{it}^{b})$
4. For each $(i = 1, \ldots, n_t)$ and $(t = 1, \ldots, T)$, we calculated the bias corrected efficiency, as: $\left(\widehat{\widehat{\phi}}_{it}\right)$

$$\widehat{\widehat{\phi}}_{it} = \hat{\phi}_{it} - bi\hat{a}s_{it}.$$

$bi\hat{a}s_{it}$ is the bootstrap estimator of bias, obtained following Simar and Wilson [38]:

$$\widehat{bias}_{it} = \left(\frac{1}{B_1}\sum_{b=1}^{B_1}\hat{\phi}_{it}^{b}\right) - \hat{\phi}_{it}. \tag{7}$$

5. We computed a truncated maximum likelihood estimation to regress the bias corrected efficiency scores $\left(\widehat{\widehat{\phi}}_{it}\right)$ against the context variables (Z_{it}) and (D_t) to obtain $\widehat{\widehat{\beta}}$ of β, $\widehat{\widehat{\delta}}$ of δ, and $\widehat{\widehat{\sigma}}_{\varepsilon}$ of σ_{ε}.
6. We replicated the following steps B_2 times to obtain a set of bootstrap estimates $\left\{\left(\widehat{\widehat{\beta}}^{b}, \widehat{\widehat{\delta}}^{b}, \widehat{\widehat{\sigma}}_{\varepsilon}^{b}\right) b = 1, \ldots, B_2\right\}$

    a. For each $(i = 1, \ldots, n_t)$ and $t = 1, \ldots, T$, draw $\widetilde{\widetilde{\varepsilon}}_{it}$ from the $N(0, \widehat{\widehat{\sigma}}_{\varepsilon}^{2})$ distribution with left-truncation at $\left(1 - \widehat{\widehat{\beta}}Z_{it} - \widehat{\widehat{\delta}}D_t\right)$.
    b. For each $(i = 1, \ldots, n_t)$ and $t = 1, \ldots, T$, compute $\widetilde{\widetilde{\phi}}_{it} = \widehat{\widehat{\beta}}Z_{it} + \widehat{\widehat{\delta}}D_t + \widetilde{\widetilde{\varepsilon}}_{it}$
    c. Use the maximum likelihood method to estimate the truncated regression of $\left(\widetilde{\widetilde{\phi}}_{it}\right)$ on (Z_{it}) and (D_t) to obtain $\widehat{\widehat{\beta}}^{b}$ of β, $\widehat{\widehat{\delta}}^{b}$, of δ and $\widehat{\widehat{\sigma}}_{\varepsilon}^{b}$ of σ_{ε}.

7. We calculated confidence interval and standard errors for $\widehat{\widehat{\beta}}$, $\widehat{\widehat{\delta}}$ and $\widehat{\widehat{\sigma}}_{\varepsilon}$ from bootstrap distribution of $\widehat{\widehat{\beta}}^{b}$, $\widehat{\widehat{\delta}}^{b}$, and $\widehat{\widehat{\sigma}}_{\varepsilon}^{b}$

This analysis was carried out for total efficiency, for economic efficiency, and for social efficiency. In addition, for robustness, a sensitivity analysis was proposed for different input and output variables in the DEA model and, later, in the second stage, we re-estimated the truncated regression for two possible alternative models.

3.2. Variables and Data

3.2.1. DEA Specification

The choice of inputs and outputs is of paramount importance for DEA methodology. There are no standard tools to select the substantial SE inputs and outputs.

Following the works of Retolaza et al. [39], Guzman et al. [40], Lee and Seo [6], Basharat et al. [41], Gutierrez-Nieto et al. [26], and Martínez-Campillo et al. [29] for different types of SE and various work in the fields of strategic management (e.g., [12,42]) and even some oriented the study of SWs [7], we proposed the following efficiency indicators (Table 1).

Table 1. Inputs and outputs data envelopment analysis (DEA) model.

Categories	Variables
Inputs	Fixed tangible assets (I)FA, operating costs (I)OC, and salary cost subsidies (I)SCS.
Outputs	Operational Output: Net income (O)NI. Social Outputs: disadvantaged employees (O)DE and professional activity support units subsidies (O)PAS.

Source: own elaboration.

Regarding the measurement of economic efficiency, most two-stage models like the one we proposed, use financial ratios as variables in the second stage, and monetary items of financial statements are used in DEA models as inputs and outputs in the first stage [32].

Measuring the efficiency of SE, at least from a social point of view, remains to be unresolved in literature. Measuring social value is more complicated than that of economic value, which can be done objectively using financial statements data.

Due to the lack of standardized values when assessing social value, we have taken into account as a measure of social value those indicators that can be quantified and the data of which are available for the whole sample, always within the possibilities of the information provided by public administrations. We believe it is more useful to evaluate as many SWs as possible than to make efforts to more comprehensively calculate the social value for a smaller number of SWs. This limitation should be considered as the result may not reflect the full social value generated by SWs.

Input Variables

An SW is a company engaged in the production of goods or services. In line with literature, as for the variables that we consider best represent the inputs used by these organizations to achieve social and economic efficiency, we selected: fixed tangible assets, salary cost subsidies, and operating costs.

Fixed tangible asset (I)FA, represents the physical capital of an organization; operating assets; or property, plant, and equipment. These are fundamental to the day-to-day operation of SWs and to generate employment and carry out their economic activity. Different studies have used these variables as an input in the DEA, for example, [39,43,44].

Salary cost subsidies (I)SCS, are grants received according to the number of workers with disabilities hired and is an input for the achievement of their social and economic objectives. Subsidies are a variable used assiduously in the development of performance models in the nonprofit sector [14,45]. It is also consistent with other studies that used grants as an input in their DEA calculations, for example, Staessens et al. [7] for a Flemish SW group. SEs are highly dependent on grants, from governments or institutions. As a result, this implies low financial independence, and in particular, young SEs strive to get grants. On the other hand, already stabilized companies tend to seek financial independence from them. Therefore, the grants variable should be used to measure its efficiency, and caution is required in its interpretation [6]. We used the salary cost subsidy, being their main source of funding, as an input and the professional activity support unit subsidy as an output.

Operating costs (I)OC include the cost of goods sold, personnel expenses, depreciation, and other operating expenses in the profit and loss statement. They are a necessary input to carry out their economic activity and to employ people with disabilities. Many other studies have used operating costs as an input variable in DEA models to evaluate efficiency, for example, [41,46].

Output Variables

We broke down the outputs into two types: operational and social. As an operational output, we used net income (O)NI. It is the income received by SWs from their economic activities, usually from the sale of goods and the provision of services. It is a classic measure for valuing economic production [40–42,46].

The social mission of the SWs is to provide disabled people with paid work suitable to their personal characteristics and to facilitate, with the necessary personal and social adjustment services (psychological and health care, rehabilitation, training, etc.), their integration into the ordinary employment regime. The social output is given by the number of employees with disabilities and the support units subsidies received.

The number of disadvantaged employees (O)DE, is used to assess the social performance of the SWs. Whenever possible, these workers would eventually move to the ordinary job market, but very few manage to do so. Battilana et al. [4] used the percentage of workers who found ordinary work for French WISEs. Staessens et al. [7] used the same variable for Flemish SWs, and Retolaza et al. [39] did the same for Spanish WISEs.

The professional activity support units subsidies (O)PAS, were used as a proxy for personal and social adjustment services provided to disabled workers by the SWs. A similar type of grant was used in the work of Battilana et al. [4].

Table 2 shows the descriptive statistics and the Spearman rank correlation test between the variables used for the period 2008–2017. We should mention the effort made trying to complete, clean, and debug the sample. We collected financial data from an annual account SABI database, and all other data were provided by the Xunta de Galicia (Consellería de Economía, Emprego and Industria). We had to dispense with some entities and finally work with 609 observations corresponding to a different number of SWs for each analyzed year, of which 404 were FPL and 205 were NPL. We must show that the detection and correction of outliers has been a complicated process since a nonhomogeneous DMU can result in an outlier (we used outlier.ap from the "Benchmarking" package implemented in the R software). Highly productive outliers can affect results as the reference frontier is built from these. Non-productive DMUs information does not affect overall results [47]. Our model complied with the general rule that the total number of observations must be at least three times that of the total variables.

Table 2 also displays the correlation coefficients of input and output variables. We can see positive correlations between the inputs and outputs, satisfying the isotonicity property that an output does not decrease with increase in the input. The correlation coefficient between inputs and outputs ranged from 0.1980 to 0.9226. The correlation between input variables ranged from 0.6540 to 0.8497, and between output variables, from 0.2054 to 0.8444. Therefore, following Lee and Seo [6], the selected inputs and outputs did not require further manipulation, such as variable reduction or dimension reduction techniques.

Table 2. Descriptive statistics and Spearman rank correlation matrix of inputs and outputs.

2008–2017	(I)FA	(I)OC	(O)DE	(I)SCS	(O)NI	(O)PAS
Mean	454,558.94	748,889.57	23.44	91,810.79	678,153.85	5425.87
Median	69,691.69	338,598.9	12.00	41,403.25	301,139.59	0.00
Std dev	1,131,706.93	1,129,725.06	34.01	150,899.83	1,078,732.67	20,145.76
Min	0.00	3724.01	0.50	313.75	0.00	0.00
Max	7,424,616.80	8,003,012.69	218.00	1,340,483.37	8,253,007.25	212,627.70
Obs. Nº	609	609	609	609	609	609
Spearman correlation matrix						
(I)FA	1	0.6709 ***	0.6003 ***	0.6540 ***	0.6383 ***	0.1980 ***
(I)OC	0.6709 ***	1	0.8444 ***	0.8497 ***	0.9671 ***	0.2433 ***
(O)DE	0.6003 ***	0.8444 ***	1	0.9226 ***	0.7960 ***	0.3515 ***
(I)SCS	0.6540 ***	0.8497 ***	0.9226 ***	1	0.8003 ***	0.3316 ***
(O)NI	0.6383 ***	0.9671 ***	0.7960 ***	0.8003 ***	1	0.2054 ***
(O)PAS	0.1980 ***	0.2433 ***	0.3515 ***	0.3316 ***	0.2054 ***	1

Source: own elaboration. *** Indicate significance level $\alpha = 0.01$.

3.2.2. Measurement of the Efficiency Determinants

We used the following variables to examine the determinants of efficiency in SWs. The SABI database was consulted.

1. Organization size (LNTA), natural logarithm of the total assets in millions of Euros.
2. Organization age (LNAGE), natural logarithm of the number of years SW has until 2017.
3. Liquidity (LQ), relationship between the current assets and current liabilities, as a percentage.
4. Long-term liabilities (LPL), relationship between long-term liabilities and total liabilities.
5. Return on assets (ROA), as a percentage (we only used it as an explanatory variable in social efficiency).
6. SW for-profit legal status (SWFPL), dummy that takes the value of "1" for-profit and "0" otherwise.
7. Group membership (GROUP), a dummy that takes the value of 1 when the SW belongs to one group and 0 in another case.

8. Composition of the board (GENDER), percentage of women on the board.
9. To end, we included dummy variables y2009, y2010, . . . , y2017 to capture technological change, the base year was 2008.

We re-engaged an extensive outliers review to try to debug environmental variable data. Table 3 then shows the descriptive statistics for non-dummy variables.

Table 3. Descriptive statistics of efficiency determinants.

Statistics	LNTA	LNAGE	LQ	LPL	ROA	GENDER
Mean	12.6481	2.0251	1.9143	0.1777	1.9180	0.1535
Median	12.7360	2.3026	1.3589	0.0846	2.730	0.0000
Std dev	1.5098	0.8624	1.7255	0.2740	16.5722	0.3200
Min	7.1134	0.0000	0.0227	0.0000	−63.3630	0.0000
Max	15.8990	3.3673	11.3591	1.6147	78.3760	1.0000

Source: own elaboration.

4. Results and Discussion

4.1. First Stage. DEA Analysis

We applied the DEA methodology set out above, CCR and BCC models, with output orientation and obtained the results shown in Figure 1.

In general, in average terms, the level of efficiency for the set of years and entities was very high. Under the constant returns model (CCR) NPL SWs had higher efficiency levels than for profit throughout the period analyzed, except for 2016 where it was slightly higher in FPL SWs.

Considering variable returns (BCC model), efficiency increased considerably with values close to 91.09% in mean terms. In this case the differences between SWs for and not-for-profit were minor, SWs NPL had higher efficiency levels than FPL throughout the period analyzed, except for 2011 where it was slightly higher in for-profit centers.

Overall, we saw a significant decrease for both types of SWs in efficiency in models in 2009, 2010, 2012, and 2013, which corresponds to the most recent crisis in Spain (2008–2013), and an increase in 2011 and the recovery period (2014, 2015, and 2016), although it fell slightly, again, in the last year, 2017. In addition, NPLs had an efficiency average for the entire analyzed period superior to FPL SWs, both under BCC and CCR.

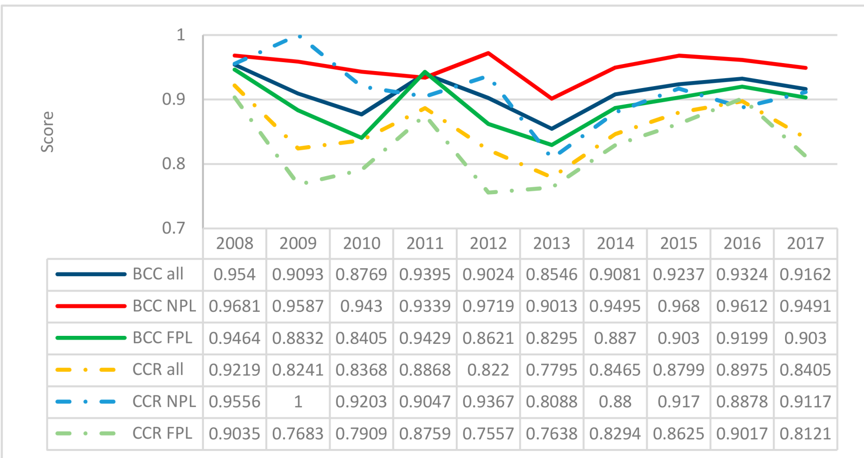


Figure 1. Efficiency mean all sheltered workshops (SW), for-profit legal (FPL), and not-for-profit legal (NPL), by year. BCC and CCR Models. Source: own elaboration.

In Figure 2, we collected the scores for each entity and year of efficiency of the model of constant returns (abscissa) and variable returns (ordered). We noted that the scores with the BCC model are always equal to or higher than those of the CCR.

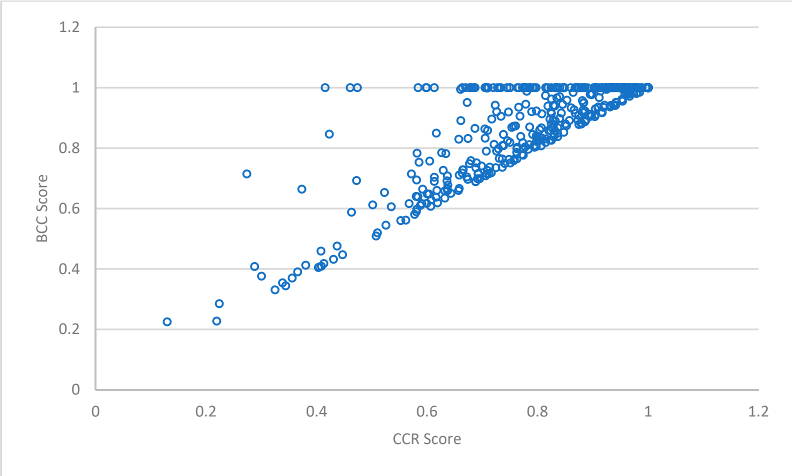


Figure 2. Technical efficiency score. Source: own elaboration.

Following on, we continude our analysis with the efficiency scores of the BCC model.

The DEA model is relatively simple to estimate but, as discussed above, has several limitations. Regardless of the objective pursued, the simple search for the most efficient units, or the projections towards the frontier, we must show that the estimator of the efficiency measure is biased from its own construction. In order to avoid the problems related to the serial correlation, we used the Simar and Wilson procedure [37] to correct the bias in the estimated efficiency score (BCC), while estimating the confidence intervals. The estimation of these values has been carried out with the function bootstrap_basic of the deaR package implemented in the R software.

Corrected efficiency scores were calculated. The rankings did not changed substantially, however, efficiency scores were generally reduced. According to the corrected scores, on average, for the entire period, the technical efficiency stood at 0.8227, which means that, from the same input levels, these entities could potentially increase their outputs by 17.73% to reach the relative maximum efficiency level. In addition, no SW, once the bootstrap was applied, got value 1. The average scores for the initial BCC model, as we saw, were 0.9109, resulting in 57.37% of fully efficient SWs.

Table 4 collects the descriptive statistics (min, max, mean, and std dev), both for the original and the corrected efficiency, for the different years and for the overall period. Like Simar and Wilson [3], corrected efficiency estimates were obtained using 2000 repetitions.

Table 4. Descriptive statistics BCC output model, original and corrected efficiency.

2008–2017	Original Efficiency	Corrected Efficiency
Min	0.2247	0.1987
Max	1	0.9772
Mean	0.9109	0.8227
Std. dev	0.1490	0.1445

Source: own elaboration.

We used the Mann–Whitney nonparametric test in order to observe if there were any differences in the efficiency scores between the models before and after the bias correction and to determine whether the bias correction helped us to improve our results. We got a value from the statistic Z = −21.38, and from the *p*-value = 0.000, therefore, we rejected the null hypothesis of equality between the efficiency scores and corrected efficiency score.

The results show that corrected efficiency scores are always lower than those of the original efficiency, as the latter do not take into account the sampling noise. Therefore, analysis based on the conventional DEA model can lead to erroneous conclusions by ignoring the bias inherent in the DEA procedure [37].

To test the robustness of DEA results, we conducted a sensitivity analysis by omitting an input or an output and then studying the results. The removed variables were: (I)FA, (I)OC, (I)SCS, and (O)PAS. The score and the biased corrected score for each model are calculated and the mean of the scores obtained are shown in Table 5. Table 6 presents the nonparametric pairwise Spearman's rank correlation test.

Table 5. Original and corrected efficiency, BCC and BCC without (I)FA, (I)OC, (I)SCS, and (O)PAS. Mean 2008–2017.

Mean 2008–2017	BCC	BCC without (O)PAS	BCC without (I)SCS	BCC without (I)OC	BCC without (I)FA
Original efficiency	0.9109	0.8618	0.8418	0.6798	0.8030
Corrected efficiency	0.8227	0.8061	0.7861	0.5934	0.7405

Source: own elaboration.

Table 6. Spearman rank correlation coefficients: original and bias-corrected efficiency.

Original Efficiency	BCC	BCC without (O)PAS	BCC without (I)SCS	BCC without (I)OC	BCC without (I)FA
BCC	1	0.8709 ***	0.8482 ***	0.7118 ***	0.8047 ***
BCC without (O)PAS	0.8709 ***	1	0.7371 ***	0.5866 ***	0.6953 ***
BCC without (I)SCS	0.8482 ***	0.737 ***	1	0.6152 ***	0.7357 ***
BCC without (I)OC	0.7118 ***	0.5866 ***	0.6152 ***	1	0.6829 ***
BCC without (I)FA	0.8047 ***	0.6953 ***	0.7357 ***	0.6829 ***	1
Corrected Efficiency	**BCC**	**BCC without (O)PAS**	**BCC without (I)SCS**	**BCC without (I)OC**	**BCC without (I)FA**
BCC	1	0.8972 ***	0.8677 ***	0.6243 ***	0.8186 ***
BCC without (O)PAS	0.8972 ***	1	0.7967 ***	0.5232 ***	0.7240 ***
BCC without (I)SCS	0.8677 ***	0.7967 ***	1	0.5251 ***	0.7361 ***
BCC without (I)OC	0.6243 ***	0.5232 ***	0.5251 ***	1	0.6875 ***
BCC without (I)FA	0.8186 ***	0.7240 ***	0.7361 ***	0.6875 ***	1

Source: own elaboration. *** Indicate significance level $\alpha = 0.01$.

Tables 5 and 6 show that the professional activity support unit subsidies, (O)PAS, and salary cost subsides, (I)SCS, were the variables that had the least influence on the level of efficiency. The Spearman's rank correlation test for models without these variables showed the highest values. The variable with the greatest effect was operating costs (I)OC, since it constituted the most important input in this type of SE. However, in general, the different models confirmed the conclusions of the original DEA model.

4.2. Second Stage. Truncated Regression Analysis

Next, we went on to analyze the impact of the context variables on management carried out by the SWs, measured through the technical efficiency levels. To do this, a bootstrapped-truncated regression with 2000 repetitions was applied following the Simar and Wilson procedure [3].

The global empirical specification of the truncated regression model was as follows,

$$\widehat{\widehat{\phi}}_{it} = \beta_0 + \beta_1 LNTA_{i,t} + \beta_2 LNAGE_{i,t} + \beta_3 LQ_{i,t} + \beta_4 LPL_{i,t} + \beta_5 SWFPL_{i,t} + \beta_6 SWFPL_i + \beta_7 GROUP_i + \delta_t time_t + \varepsilon_{it} \quad (8)$$

where $\widehat{\widehat{\varnothing}}_{it}$ represents the value of the corrected technical efficiency achieved by the SW_i in the t-period. $\beta_0, \beta_1, \beta_2, \ldots, \beta_7, \delta_1, \ldots, \delta_9$ are the parameters to be determined, and ε_{it} is the error term. The rest are the context variables considered in the study that could influence efficiency levels.

The results of the two estimated models are shown below. The first included the internal explanatory variables (total assets, age, liquidity, long-term liabilities, for-profit legal status, group, and gender). Model 2 also included the dummy variables per year to pick up changes from 2008.

Table 7 reports the results of the truncated bootstrapped regression models.

Table 7. Results of bootstrap truncated regressions, total efficiency versus context variables, Algorithm II, Simar and Wilson (2007).

Variables	Model 1			Model 2		
Alfa = 0.05	**Beta**	**LL**	**UL**	**Beta**	**LL**	**UL**
Intercept	24.2735 ***	19.3337	29.6691	22.5616 ***	18.2958	27.5236
LNTA	−1.7171 ***	−2.2057	−1.2833	−1.5881 ***	−2.0122	−1.2257
LNAGE	−1.3934 ***	−1.9607	−0.8998	−1.3263 ***	−1.8180	−0.8888
LQ	0.0524	−0.1573	0.3548	0.0839	−0.2157	0.0818
LPL	−2.9507 ***	−4.8966	−1.2247	−2.8215 ***	−4.4961	−1.3624
SWFPL	−0.3774	−1.3277	0.5872	−0.3744	−1.1998	0.4228
GROUP	−0.0003	−1.0949	1.0379	−0.0708	−0.9909	0.8328
GENDER	−0.0191	−1.5411	1.3105	−0.1265	−1.3417	1.1035
y2009				0.0233	−1.6675	1.7797
y2010				−1.6367 *	−3.4194	0.0835
y2011				−2.3511 **	−4.5430	−0.3962
y2012				0.6979	−1.0797	2.4479
y2013				0.8915	−0.7358	2.5905
y2014				0.2524	−1.4093	1.9311
y2015				−0.1480	−1.8296	1.5514
y2016				0.3288	−1.2801	2.1097
y2017				1.0496	−0.6315	2.7816
Sigma	2.6406 ***	2.2654	3.1386	2.4686 ***	2.1280	2.8703

*** Significance level $\alpha = 0.01$; ** significance level $\alpha = 0.05$; * significance level $\alpha = 0.1$. LL: lower level; UL: upper level. Source: own elaboration.

Size (LNTA) had a significant coefficient and directly related to efficiency, showing that a larger size means higher levels of efficiency. Similarly, the age coefficient (LNAGE) and long-term indebtedness coefficient (LPL) were significant and showed a positive relationship. Higher age and higher level of long indebtedness mean greater technical efficiency. In Model 2, the above variables were confirmed, and, additionally only y2011 and y2010 were significant (at 10%). During these two years the SWs experienced very important increases in aid received [22], significantly affecting overall efficiency.

Considering the results obtained in the sensitivity analysis, a robustness analysis was then carried out for the second stage of the proposed model. The efficiency scores obtained with the BCC model without salary cost subsidies and the BCC model without professional activity support unit subsidies were used in two new truncated regression estimations.

For the BCC without salary cost subsidies, (I)SCS model, as for the original model (results in Table 7), size and age had a significant and positive coefficient. The long-term indebtedness coefficient showed a positive relation, but it was not significant, and the group membership showed a significant and positive coefficient. The most notable difference with respect to the originally proposed model was that y2011 and y2010 were not significant due to the elimination of the input in the BCC model that reflected an important increase in aid received during these years. For the BCC without the professional activity support unit subsidies, (O)PAS model, the exogenous variables that affect efficiency were the same and with the same sign as in the original BCC model. The tables with the results will be available to those interested.

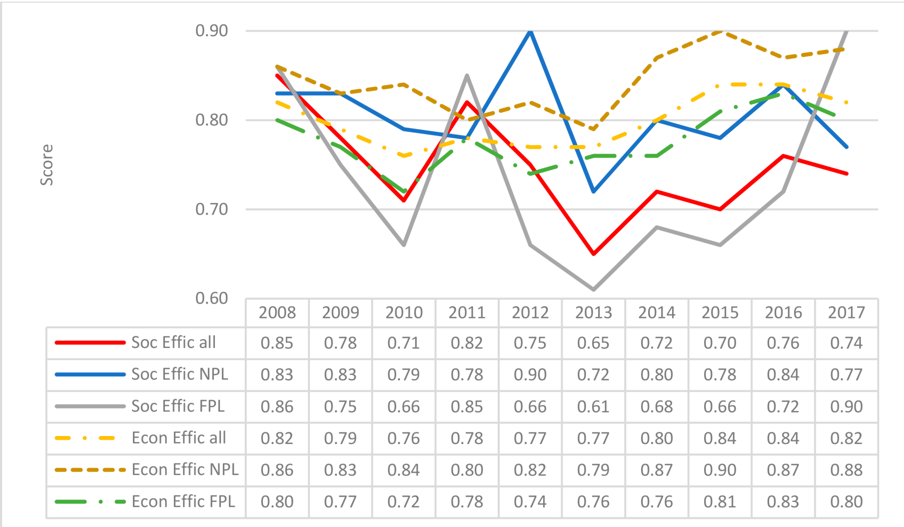
4.3. Analysis of the Effect of Context Variables on Social Efficiency and Economic Efficiency

Following Staessens et al. [7], we calculated the social and economic efficiency for all the SWs, always using the original BCC model. To calculate it, we assigned a zero weighting to the economic and social outputs, respectively. Therefore, we had two efficiency scores for each SW: economic efficiency (E-E) and social efficiency (S-R). Table 8 shows the descriptive statistics of these efficiency scores and Figure 3, the scores for social and economic efficiency for all SWs, FPLs, and NPLs.

Table 8. Descriptive statistics, social and economic efficiency, mean 2008–2017

Statistics	Social Efficiency	Economic Efficiency
Mean	0.7436	0.8001
Median	0.7733	0.8552
Std dev	0.2563	0.2212
Min	0.0752	0.0000
Max	1.0000	1.0000

Source: own elaboration.



	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Soc Effic all	0.85	0.78	0.71	0.82	0.75	0.65	0.72	0.70	0.76	0.74
Soc Effic NPL	0.83	0.83	0.79	0.78	0.90	0.72	0.80	0.78	0.84	0.77
Soc Effic FPL	0.86	0.75	0.66	0.85	0.66	0.61	0.68	0.66	0.72	0.90
Econ Effic all	0.82	0.79	0.76	0.78	0.77	0.77	0.80	0.84	0.84	0.82
Econ Effic NPL	0.86	0.83	0.84	0.80	0.82	0.79	0.87	0.90	0.87	0.88
Econ Effic FPL	0.80	0.77	0.72	0.78	0.74	0.76	0.76	0.81	0.83	0.80

Figure 3. Social and economic mean efficiency scores, all entities, FPL and NPL, BCC model, by year 2008–2017. Source: own elaboration.

In regards to economic efficiency, it should be noted that after calculating the average score of the SW NPLs, this was 0.85, higher than the average of 0.78 of the SW FPL. Despite not being profit-making and against expectations, SW NPLs achieved a better economic return than FPLs, with an average difference of 6.08%. This result is significant (according to the Mann–Whitney test, differences were significant, Z = 3.0688, p-value = 0.0020).

In regards to social efficiency, the average NPL SWs score was 0.80 and 0.71 for SW FPLs. The result indicates that NPLs performed better socially than FPL, with an average difference of 9.09%. This implies that the NPL strategy, in addition to generating better economic results, also do so from a social point of view. This result was significant (according to the Mann–Whitney test, differences were significant Z = 4.5449, p-value = 0.000).

Next, we searched for synergy between overall social and economic performance in SWs by analyzing the correlation between both variables. The Spearman's coefficient showed that overall social and economic efficiency scores were positively and significantly correlated ($\rho_{social,economic} = 0.1873$; $p = 0.000$). A positive sign suggests the existence of compatibility between them. The coefficient was low and significantly different from zero at the 1% level, indicating a slight association between both variables in SWs.

Next, we studied the relevance of each of the context variables in economic and social efficiency separately. Tables 9 and 10 presents the results of bootstrap truncated regressions following the Algorithm II of Simar and Wilson, using economic efficiency and social efficiency as a dependent variable versus context variables respectively.

Table 9. Results of bootstrap truncated regressions, economic efficiency versus context variables, Algorithm II, Simar and Wilson (2007).

Variables	**Model 1**			**Model 2**		
Alfa = 0.05	**Beta**	**LL**	**UL**	**Beta**	**LL**	**UL**
Intercept	46.4511 ***	55.9958	77.2642	67.3823 ***	56.5432	77.7192
LNTA	−3.4519 ***	−6.1745	−4.2314	−5.1784 ***	−6.1714	−4.2560
LNAGE	−1.3536 ***	−2.8443	−1.0094	−1.9091 ***	−2.9243	−1.0319
LQ	−0.0629 *	−0.5846	0.3650	−0.1194	−0.4165	0.0540
LPL	2.9167 ***	2.1467	7.6136	5.1938 ***	2.4795	7.8869
SWFPL	0.5302	−1.4825	2.7222	0.5680	−1.3888	2.6328
GROUP	−1.1852	−4.3161	0.5269	−1.7569	−4.2108	0.4153
GENDER	−0.5744	−3.6226	2.0431	−0.5952	−3.4124	1.8393
ESOCIAL	−0.3039	−1.2706	0.5110	−0.4193	−1.3075	0.3482
y2009	-	-	-	−0.4348	−4.3032	3.2700
y2010	-	-	-	−6.3291 ***	−10.6680	−2.3844
y2011	-	-	-	−6.5288 ***	−11.7440	−2.2137
y2012	-	-	-	0.7621	−2.5362	4.5915
y2013	-	-	-	−0.1183	−3.3263	3.8130
y2014	-	-	-	−0.8193	−4.5379	2.7282
y2015	-	-	-	−0.8248	−4.4724	2.7497
y2016	-	-	-	0.6024	−2.9285	4.2269
y2017	-	-	-	0.7150	−2.9747	4.4056
Sigma	5.9566 ***	5.3098	6.8965	5.7662 ***	5.1451	6.6305

*** Significance level α = 0.01; * significance level α = 0.1. LL: lower level; UL: upper level. Source: own elaboration.

Table 10. Results of bootstrap truncated regressions, social efficiency versus context variables, Algorithm II, Simar and Wilson (2007).

Variables	**Model 1**			**Model 2**		
Alfa = 0.05	**Beta**	**LL**	**UL**	**Beta**	**LL**	**UL**
Intercept	70.7864 ***	60.4859	80.8856	65.0412 ***	56.6969	76.2722
LNTA	−5.0647 ***	−5.9430	−4.2233	−4.9068 ***	−5.8185	−4.1033
LNAGE	−3.5144 ***	−4.5655	−2.6810	−3.4802 ***	−4.3990	−2.6289
LQ	0.3574 *	−0.0846	0.7813	0.3266	−0.2077	0.1808
LPL	−4.9849 ***	−8.0953	−2.1213	−4.2229 ***	−7.1161	−1.4886
Roa	−0.0595 ***	−0.1003	−0.0196	-0.0298 **	−0.0557	−0.0042
SWFPL	−1.2553	−3.1447	0.6139	−1.2562	−2.9459	0.4683
GROUP	−1.3558	−3.5808	0.7189	−1.4234	−3.5203	0.5309
GENDER	0.1394	−2.5486	2.6665	0.4627	−2.1871	2.8170
y2009	-	-	-	1.1201	−2.2394	4.6458
y2010	-	-	-	−2.1788	−5.8940	1.5299
y2011	-	-	-	−3.1427	−7.3759	0.8307
y2012	-	-	-	2.2313	−1.2221	5.9824
y2013	-	-	-	3.0319 *	−0.2699	6.5761
y2014	-	-	-	2.8064	−0.3528	6.3708
y2015	-	-	-	2.5235	−0.8731	6.0044
y2016	-	-	-	3.7250 **	0.5034	7.2836
y2017	-	-	-	4.6775 ***	1.3953	8.3349
Sigma	5.3449 ***	4.7405	6.0410	5.1882 ***	4.6604	5.86413

*** Significance level α = 0.01; ** significance level α = 0.05; * significance level α = 0.1. LL: lower level; UL: upper level. Source: own elaboration.

When we used economic efficiency as a dependent variable (Table 9), the size (LNTA), age (LNAGE), and liquidity coefficient (LQ)—the latter only 10%—were significant and positive. The greater the size, age, and liquidity, the more economic efficiency (E-E), long-term liabilities (LPL) was also significant but its effect was inverse. Model 2 displays the same significant variables with the same sign. y2010 and y2011 were also significant and positively related to efficiency economics. We introduced a variable (ESOCIAL) in both models that collected the social efficiency for each SW, in both, the coefficient was negative but in neither significant. Therefore, we cannot say that social efficiency significantly affects the level of economic efficiency.

Social efficiency, Table 10, mirrors the results of the two regression models. Size and seniority were positively and significantly related to efficiency, coinciding with the economic efficiency model, but we also had a positive and significant relationship between ROA and LPL. We included the ROA in the social efficiency study as we considered that it could affect social performance. If the SW is not profitable, it can hardly meet its social objective. Model 2 shows the same significant variables with the same sign, and furthermore, inversely related and significant: y2013, y2016, and y2017. The year 2013 stands out among the economic exercises that negatively affected social efficiency where, as we saw, there have been very significant reductions in social efficiency, especially for the FPL, as a result of the policy of subsidy reductions initiated in 2012. In 2017 there was also a decrease in social efficiency, especially for NPLs. All these exercises were paradoxically at the end of the crisis (2013) and the period of economic recovery (2016 and 2017), which did not result in the improvement of social efficiency.

We agree with Martínez Franco and Guzmán Raja [14] that the positive relationship between long-term indebtedness and total efficiency could be explained by the patrimonial strength of the SWs. Greater confidence on the part of financial institutions implies a greater capacity to obtain financing, an important issue for these entities with little capacity for self-financing. As for the inverse relationship between long-term indebtedness and economic efficiency, the explanation could be because the most economically profitable SWs are those with the lowest short-term indebtedness [21,22].

5. Conclusions

This study analyzed the efficiency level of SWs for the period 2008–2017 by tracking efficient frontiers using the nonparametric DEA technique. The study was complemented by a semiparametric two-stage approach, applying Simar and Wilson's Algorithm II [3] to assess the possible relevance of environmental variables in the efficiency of these organizations calculated under the variable returns to scale hypothesis (BCC model). In addition, by separating this efficiency into social and economic, we valued the effects of these environmental variables on each of them.

The main conclusions of our work for the proposed efficiency model indicate that SWs achieved high pure technical efficiency values of 0.9109. In terms of the differentiation between social and economic efficiency, the SWs got better scores in the latter, thus having greater opportunities for improvement in social aspects. The results yielded similar values to those achieved in previous studies (such as Staessens et al. [7]), despite differences in the specification of inputs and/or outputs.

Subsequently, applying Simar and Wilson's [37] method, we corrected the bias in the efficiency estimates. The scores were generally reduced, with an average of 0.8227, without altering the order.

As for temporal evolution, overall efficiency decreased slightly, with certain ups and downs, over the study period. Economic efficiency remained more or less constant, while in social efficiency there were significant decreases. Our study also revealed that NPL SWs are more efficient, socially and economically, and not more fragile than FPL SWs.

The two-stage DEA analysis showed that size and age variables are positively related to total efficiency as well as to economic and social variables individually. The long-term level of indebtedness reduces the likelihood that the SW will obtain optimal economic efficiency that allows it to be at the frontier of best practice, while acting in reverse on total and social efficiency. It was not possible to draw conclusions regarding the variables liquidity, gender, membership of a group, and the character with or without profit, as they were not statistically significant. The two robustness analyses carried out, one at each stage of the proposed methodology, confirmed the results.

We showed that there is a positive and significant relationship between social and economic efficiency, although the intensity of it is slight. As for the meaning of this relationship, economic productivity, as measured through the ROA, is positively associated with social efficiency, the same results that Battilana et al. [4] and Staessens et al. [7] obtained. However, we found no evidence as to the influence of social aspects on economic efficiency. A SE, whether profit-making or not, may only reinvest surpluses derived from its activity if it manages to survive. Economic aspects are a prerequisite for being able to fulfil their social mission in a sustainable way by freeing up resources [2,4,6,20].

Considering our findings, a set of recommendations can be made for managers, investors (government and private investors), and other interest groups to improve the SWs' social and economic performance.

Policy makers can use this approach in their decision-making process and as a mechanism for legitimizing their decisions by allocating their resources more efficiently. Using the proposed approach to measure the social and economic performance of SWs allows public authorities to distinguish between socially and economically efficient and inefficient entities and would allow them to assess the impact of their policies.

As a result, governments could reallocate resources to those more efficient entities and, at the same time, serve as a stimulus for the SWs themselves to improve their efficiency. All this would allow the development of more personalized support programs, which would benefit individual SWs should encourage them to carry out their activity responsibly, since both social and economic efficiency would be increased.

Measurement of social performance is also important to involve private capital in social change. Investors and funders are often reluctant to invest in SWs due to a lack of information on their performance. They will only support those SWs that are economically sustainable in order to fulfil their social mission in society, so this methodology could be used in their decision-making processes.

Finally, these disclosure requirements have also been proposed by other interest groups (volunteers, employees, local community, customers, media, and the general public) who request that SWs be responsible in their activities and ensure adequate accountability and transparency.

In addition to these external stakeholders, companies themselves also need information to improve their performance. Through efficiency evaluation, the internal structure of SWs was explored, identifying the main causes of inefficiency. The measurement of social performance should be integrated into the strategic management of the organization, as it would serve to identify strengths and weaknesses and would be an instrument to aid decision-making.

Author Contributions: Conceptualization, J.M.M.-S. and M.-C.L.-P.; methodology, J.M.M.-S., A.I.-C., and M.-C.L.-P.; software, M.-C.L.-P. and A.I.-C.; validation, J.M.M.-S., M.-C.L.-P., and A.I.-C.; formal analysis, J.M.M.-S., M.-C.L.-P., and A.I.-C.; investigation, J.M.M.-S., M.-C.L.-P., and A.I.-C.; resources, J.T.M.; data curation, J.M.M.-S., M.-C.L.-P., and A.I.-C.; writing—original draft preparation, M.-C.L.-P.; writing—review and editing, J.M.M.-S., M.-C.L.-P., and A.I.-C.; visualization, J.M.M.-S., M.-C.L.-P., and A.I.-C.; supervision, J.M.M.-S., M.-C.L.-P., and A.I.-C.; project administration, J.M.M.-S., M.-C.L.-P., and A.I.-C.; funding acquisition, J.M.M.-S., M.-C.L.-P., J.T.M., and A.I.-C. All authors have read and agreed to the published version of the manuscript. Authorship must be limited to those who have contributed substantially to the work reported.

Funding: This research received no external funding.

Acknowledgments: In this section you can acknowledge any support given which is not covered by the author contribution or funding sections. This may include administrative and technical support, or donations in kind (e.g., materials used for experiments).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. INE El Empleo de las Personas con Discapacidad. Available online: https://www.ine.es/CDINEbase/consultar.do?mes=&operacion=El+empleo+de+las+personas+con+discapacidad&id_oper=Ir (accessed on 3 February 2020).
2. Bellostas, A.J.; López-Arceiz, F.J.; Mateos, L. Social Value and Economic Value in Social Enterprises: Value Creation Model of Spanish Sheltered Workshops. *Voluntas* **2016**, *27*, 367–391. [CrossRef]
3. Simar, L.; Wilson, P.W. Estimation and inference in two-stage, semi-parametric models of production processes. *J. Econom.* **2007**, *136*, 31–64. [CrossRef]
4. Battilana, J.; Sengul, M.; Pache, A.-C.; Model, J. Harnessing productive tensions in hybrid organizations: The case of Work Integration Social Enterprises. *Acad. Manag. J.* **2015**, *58*, 1658–1685. [CrossRef]
5. Dia, M.; Bozec, R. Social enterprises and the performance measurement challenge: Could the data envelopment analysis be the solution? *J. Multi-Crit. Decis. Anal.* **2019**, *26*, 265–271. [CrossRef]
6. Lee, P.; Seo, Y.W. Directions for Social Enterprise from an Efficiency Perspective. *Sustainability* **2017**, *9*, 1914. [CrossRef]
7. Staessens, M.; Kerstens, P.J.; Bruneel, J.; Cherchye, L. Data Envelopment Analysis and Social Enterprises: Analysing Performance, Strategic Orientation and Mission Drift. *J. Bus. Ethics* **2018**, *159*, 325–341. [CrossRef]
8. Hjalmarsson, L.; Kumbhakar, S.C.; Heshmati, A. DEA, DFA and SFA: A comparison. *J. Prod. Anal.* **1996**, *7*, 303–327. [CrossRef]
9. Murillo-Zamorano, L.R. Economic Efficiency and Frontier Techniques. *J. Econ. Surv.* **2004**, *18*, 33–77. [CrossRef]
10. Deville, A. Branch banking network assessment using DEA: A benchmarking analysis—A note. *Manag. Account. Res.* **2009**, *20*, 252–261. [CrossRef]
11. Rouse, P.; Putterill, M.; Ryan, D. Integrated performance measurement design: Insights from an application in aircraft maintenance. *Manag. Account. Res.* **2002**, *13*, 229–248. [CrossRef]
12. Banker, R.D.; Natarajan, R. Evaluating Contextual Variables Affecting Productivity Using Data Envelopment Analysis. *Oper. Res.* **2008**, *56*, 48–58. [CrossRef]
13. Simar, L.; Wilson, P.W. Two-stage DEA: Caveat emptor. *J. Prod. Anal.* **2011**, *36*, 205–218. [CrossRef]
14. Franco, C.M.M.; Raja, I.G. Medida de la eficiencia en entidades no lucrativas: Un estudio empírico para fundaciones asistenciales. *Rev. Contab.* **2014**, *17*, 47–57. [CrossRef]
15. Solana, J.; Ibáñez, N.; Benito, B. Determinantes de la eficiencia en las fundaciones españolas. *Rev. Contab.* **2017**, *20*, 176–194. [CrossRef]
16. Martínez-Campillo, A.; Fernández-Santos, Y. What about the Social Efficiency in Credit Cooperatives? Evidence from Spain (2008–2014). *Soc. Indic. Res.* **2017**, *131*, 607–629. [CrossRef]
17. Salas-Velasco, M. Measuring and explaining the production efficiency of Spanish universities using a non-parametric approach and a bootstrapped-truncated regression. *Scientometrics* **2020**, *122*, 825–846. [CrossRef]
18. Huber, G.P.; Sutcliffe, K.; Miller, C.; Glick, W.H. Understanding and predicting organizational change. In *Organizational Change and Redesign*; Huber, G.P., Glick, W.H., Eds.; Oxford University Press: New York, NY, USA, 1993.
19. González, M.; Rúa, E. Análisis de la eficiencia en la gestión de las fundaciones: Una propuesta metodológica. *CIRIEC-Esp. Rev. Econ. Pública Soc. Coop.* **2007**, *57*, 117–149.
20. Montagud, M.H. *Las Empresas Sociales: Un Grupo en Expansión en el Ámbito de la Economía Social*; Identificación y Análisis de las Características Identitarias de la Empresa Social Europea y su Aplicación a la Realidad de los Centros Especiales de Empleo de la Economía Española; Universitat de València: Valencia, Spain, 2015; Available online: http://purl.org/dc/dcmitype/Text (accessed on 5 February 2020).
21. Montagud, M.H.; Campos, J.L.M. Identificación y análisis de las características identitarias de la empresa social europea: Aplicación a la realidad de los Centros Especiales de Empleo de la economía española. *CIRIEC-Esp. Rev. Econ. Pública Soc. Coop.* **2016**, *87*, 295–326. [CrossRef]
22. López-Penabad, M.-C.; Maside-Sanfiz, J.M.; Torrelles-Manent, J. Análisis económico y social de los centros especiales de empleo: Un estudio en Galicia. *REVESCO Rev. Estud. Coop.* **2019**, *132*, 169–194. [CrossRef]
23. Raja, I.G.; Garces, A.H.; Carvajal, C.R. Efficiency analysis by programs in the field of social economy: The case of Asturias. *REVESCO-Rev. Estud. Coop.* **2013**, *110*, 129–162. [CrossRef]
24. Smith, W.K.; Lewis, M.W. Toward a Theory of Paradox: A Dynamic equilibrium Model of Organizing. *Acad. Manag. J.* **2011**, *36*, 381–403. [CrossRef]

25. Jay, J. Navigating paradox as a mechanism of change and innovation in hybrid organizations. *Acad. Manag. J.* **2013**, *56*, 137–159. [CrossRef]
26. Gutiérrez-Nieto, B.; Serrano-Cinca, C.; Mar Molinero, C. Microfinance institutions and efficiency. *Omega* **2007**, *35*, 131–142. [CrossRef]
27. Worthington, A.C. Measuring Technical Efficiency in Australian Credit Unions. *Manch. Sch.* **1999**, *67*, 231–248. [CrossRef]
28. Glass, J.C.; McKillop, D.G.; Quinn, B.; Wilson, J. Cooperative bank efficiency in Japan: A parametric distance function analysis. *Eur. J. Financ.* **2014**, *20*, 291–317. [CrossRef]
29. Martínez-Campillo, A.; Fernández-Santos, Y.; del Pilar, S.-F. How Well Have Social Economy Financial Institutions Performed During the Crisis Period? Exploring Financial and Social Efficiency in Spanish Credit Unions. *J. Bus. Ethics* **2018**, *151*, 319–336. [CrossRef]
30. Nielsen, S.; Huse, M. The contribution of women on boards of directors: Going beyond the surface; Corporate Governance: An international review. *Corp. Gov. Int. Rev.* **2010**, *18*, 136–148. [CrossRef]
31. Ebrahim, A.; Battilana, J.; Mair, J. The governance of social enterprises: Mission drift and accountability challenges in hybrid organizations. *Res. Organ. Behav.* **2014**, *34*, 81–100. [CrossRef]
32. Belu, C. Ranking corporations based on sustainable and socially responsible practices. A data envelopement analysis (DEA) approach. *Sustain. Dev.* **2009**, *17*, 257–268. [CrossRef]
33. Mousavi, M.M.; Ouenniche, J.; Tone, K. A comparative analysis of two-stage distress prediction models. *Expert Syst. Appl.* **2019**, *119*, 322–341. [CrossRef]
34. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
35. Banker, R.D.; Charnes, A.; Cooper, W.W. Some models for estimating technical and scale inefficiencies in Data Envelopment Analysis. *Manag. Sci.* **1984**, *30*, 1078–1092. [CrossRef]
36. Charnes, A.; Cooper, W.W.; Lewin, A.Y.; Seiford, L.M. *Data Envelopment Analysis: Theory, Methodology, and Applications*; Springer: Dordrecht, The Netherlands, 1994; ISBN 978-94-011-0637-5.
37. Simar, L.; Wilson, P.W. A general methodology for bootstrapping in non-parametric frontier models. *J. Appl. Stat.* **2000**, *27*, 779–802. [CrossRef]
38. Simar, L.; Wilson, P.W. Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models. *Manag. Sci.* **1998**, *44*, 49–61. [CrossRef]
39. Retolaza, J.L.; San-José, L.; Araujo, A. La Eficiencia como reto de las Empresas de Inserción. *REVESCO Rev. Estud. Coop.* **2014**, *115*, 159–185. [CrossRef]
40. Raja, I.G.; Lario, N.A.; De Lema, D.G.P. La eficiencia técnica como medida de rendimiento de las cooperativas agrarias. *CIRIEC-Esp. Rev. Econ. Pública Soc. Coop.* **2006**, *55*, 289–311.
41. Basharat, B.; Hudon, M.; Nawaz, A. Does Efficiency Lead to Lower Prices? A New Perspective from Microfinance Interest Rates: Efficiency and Interest Rates in Microfinance. *Strateg. Chang.* **2015**, *24*, 49–66. [CrossRef]
42. Chen, C.-M.; Delmas, M.; Lieberman, M.B. Production frontier methodologies and efficiency as a performance measure in strategic management research. *Strateg. Manag. J.* **2015**, *36*, 19–36. [CrossRef]
43. Halkos, G.; Tzeremes, N. The effect of foreign ownership on SMEs performance: An efficiency analysis perspective. *J. Prod. Anal.* **2010**, *34*, 167–180. [CrossRef]
44. Rodríguez-Pérez, G.; Slof, J.; Solà, M.; Torrent, M.; Vilardell, I. Assessing the Impact of Fair-Value Accounting on Financial Statement. *Abacus* **2011**, *47*, 61–84. [CrossRef]
45. Marcuello, C. Análisis de la conducta de la eficiencia de las organizaciones no gubernamentales españolas. *Econ. Coop. Desarro.* **1999**, *778*, 181–196.
46. Gutiérrez-Nieto, B.; Serrano-Cinca, C.; Mar Molinero, C. Social efficiency in microfinance institutions. *J. Oper. Res. Soc.* **2009**, *60*, 104–119. [CrossRef]
47. Astudillo, D.V.A. *Medición de la Eficiencia Estática y Dinámica de las Universidades Mediante Métodos: No Paramétricos*; Aplicación a las Universidades Públicas Ecuatorianas; Universidad de Sevilla: Sevilla, Spain, 2016; Available online: http://purl.org/dc/dcmitype/Text (accessed on 3 March 2020).