Do public funds increase the efficiency of the Italian theatrical firms? A parametric and a non parametric approach

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Abstract

In Italy, as in many other European countries, the performing arts (PA) are publicly subsidised. Italian PA subsidies are ensured by a Parliamentary Law that in 1985 established the Fund for the Performing Arts (FUS). The main aim of this research is to measure the impact of the FUS allocation to technical efficiency of Italian performing arts firms, since firms that receive less or no public funds can be either more or less efficient. In the first case in order to stay in the market, in the second case because public funds guarantee more cash to them. Data are derived from the AIDA dataset carried out by Bureau van Dijk and from the annual relationship of the *Fondo Unico per lo Spettacolo* over the period 2006-2014. The results obtained using both stochastic frontier approaches and double bootstrap data envelopment analysis models confirm our hypotheses based on factors (capital and labour) and firm characteristics (size, age and area). The results show that technological progress is not present for the theatrical Italian sector, providing support to the presence of Baumol's disease in the sector, and that small firm size and sector of activities (Operas, Theatres, etc.) influence firm efficiency. The impact of public funds on the technical efficiency of the Italian theatrical firms is positive and significant in both approaches, than since theatres efficiency could be increased at least by 25%, policy makers could take work on public incentives.

1. Introduction

In the last years there has been an increasing attention to the firms' performance in the cultural sector, by studying both firms productivity and firms technical (in)efficiency in different cultural activities. The determinants of technical efficiency have been studied for theatre (Fazioli and Filippini, 1997; Taalas, 1997; Zieba, 2011; and Zieba and Newman, 2013), museums (Mairesse and Vanden Eeckaut, 2002; Bassi and Funari, 2004), performing arts sector (Castiglione et al. 2016), and public historical archives (Guccio et al., 2014). The last two works also refer to Italy.

In the last years, a lot of attention is devoted to the subsidisation of the cultural sector in different countries, especially due to the crises of the public finance. In Italy, the subsidisation of the "entertainment sector" is ensured by a Parliamentary Law (n.163), approved on the 30 April 1985, that established the Fund for the Performing Arts (Fondo Unico per lo Spettacolo-FUS). The intention of the government was to insure stability and continuity for all cultural activities via the FUS. However, the crises of Italian public finance and the consequent reduction of subsidies have made the use of public resources a central theme, especially in the management of opera houses (Castiglione and Infante, 2017).

Despite the importance and the discussion on the public funds there is a lack in the empirical literature to measure the impact of public funds on the performance of firms operating in the cultural sector. By using a panel of 168 Italian firms over the period 2006-2014, the aim of this work is to fill this lacunae and to empirical measure the impact of subsides on the efficiency of a set of Italian cultural firms (Lyric-Symphonic Foundation, Theatre of Tradition, Lyrics, Permanent Public Theatres, Permanent Private Theatres, Permanent Innovative Theatres, Theatre Companies) that are subject to publish the balance sheet data.

To reach this aim we apply the stochastic frontier approaches (SFA), in particular those developed by Aigner et al. (1977), Battese and Coelli (1995), and Greene (2005) which recognise not only the technical inefficiency component (deviations below the optimal output level) but also the fact that random shocks beyond producers' control may affect the production output. Estimation of technical efficiency using SFA allows us not only to appraise technical efficiency scores but also to measure output elasticities and returns to scale of the theatrical sector. The technical efficiency can be also measured using an output-oriented Data Envelopment Analysis (DEA). The purpose is to compare the TE scores obtained in the parametric stochastic production frontier with the non-parametric approach. We estimate an output-oriented technical efficiency (TE) under variable returns to scale technology (Färe et al. 1989, Färe et al. 1994). The difference between SFA and DEA methods lies in defining the efficient frontier (i.e. the most efficient firms in the sample), which must be obtained or estimated using the sample data.

As highlighted by Castiglione, Infante and Zieba (2016) performing arts companies in Italy are very heterogeneous with regard to localization, size, quality and institutional setting of the firm. The companies may operate in different regions with various environmental factors and characteristics that are only partially observed. Thus, we apply, similarly to Pieri and Zaninotto (2013), and Castiglione et al. (2016), the SFA techniques of Greene (2005) that control for the unobserved heterogeneity that is not related to the (in)efficiency but rather to the specific characteristics of the firms.

The remainder of the paper is structured as follows. Section 2 introduces the literature to which this work refers, section 3 describes the economic model setting, whilst section 4 briefly presents the dataset. Section 5 encompasses the methodology and the empirical approach used to evaluate technical efficiency, and section 6 focuses on the results. Some conclusions are presented in Section 7.

2. Previous research

In the current literature there are some works that focus on technical efficiency in the PA sector. Taalas' (1997) results suggest that, in managing Finnish theatre, inputs are not combined in optimal proportions in light of prevailing market prices, the relative shares of inputs utilisation vary when output expands, and there are scale economies in the production of theatrical performances. While Zieba (2011) demonstrates that theatre efficiency estimates are very sensitive to the unobserved heterogeneity of Austrian and Swiss theatres, Zieba and Newman (2013) confirm that the organisational structure has an important impact on technical efficiency of German public theatres. Mairesse and Vanden Eeckaut (2002) focus on a network of French-speaking regional museums in Belgium. Their results are not univocal. They observe that the same museums can react in very different ways, being efficient in one model and not in another. Two other studies focus on specific Spanish cultural organizations. Fernandez-Blanco and Rodriguez-Alvarez (2015) measure the allocative efficiency of the *Fundación Princesa de Asturias*, a Spanish non-governmental organization devoted to promoting cultural, scientific and humanistic values of universal heritage. Their results indicate that, although the *Fundación* is not efficient (the same output could be produced with less inputs), both technical and allocative efficiencies have clearly improved during the analysed period. Marco-Serrano (2006), using data on the *Theatrical Circuit of Valencia*, a Spanish regional theatres network, develops the concept of managerial efficiency and applies a non-parametric Data Envelopment Analysis (DEA) method. The author finds decreasing trends for the managerial efficiency, caused by the progressive incorporation of new municipal theatres into the network, due to either the existence of a saturation point or because these incorporations drastically affect the structure of the cultural production frontier.

For what concerns Italy, in the cultural sector, the attention has been limited to few works and devoted to local institutions (theatre and museum) and to public historical archives (Guccio et al. 2014). Fazioli and Filippini (1997), using data on 28 Italian theatres, localized in the Emilia Romagna region, demonstrate the presence of economies of scale and scope. Their results provide evidence to the effects that theatre shows which are already prepared should be more frequently given in different locations. Bassi and Funari (2004) focus on a set of municipal museums localized in three Italian cities: Bologna, Florence and Venice. Their results show that four out of the fifteen museums have a DEA index equal to one and therefore can be considered as relatively efficient. Within the cultural institution, Guccio et al. (2014) analyse the public archives as a primary source for historical research exhibiting quite interesting features from an economic point of view. To address such an issue the authors use a nonparametric approach to measure the efficiency in the production of archival services, and find that there are wide margins for improving Italian public historical archives average efficiency.

3. Modelling Technical Efficiency for PA firms

In this paper, we adopt a concept of an output-oriented technical efficiency (TE) because we assume that the PA firms are willing to have a best-practice level of output based on a given level of input. We define an output-oriented TE in the ratio form as the observed output to maximum output. To explain the concept of an output-oriented TE for Italian PA firms, Figure 1 shows the exmple of the production technology, which is represented by a one-output (e.g. the number of tickets sold), one-input (e.g. labour) production function. For the given production technology and the same labour, the PA firm can produce output at point R (inefficient point) or at point P (efficient point) which is located on the production frontier. The technical efficiency is then defined as the ratio equal to OR/OP which is bounded between 0 and 1. This corresponds to the Farell's (1957) radial measure of an output-oriented technical efficiency. A score of one means full TE. This is for example when a theatrical company is producing at point P instead point R, meaning that the theatre is operating on the frontier and therefore is technically efficient. A score less than one means that the firm is inefficient for the given technology and it could increase its output level by utilising the same level of input.

The technical efficiency can be measured using a fully parametric SFA (Stochastic Frontier Approach) method or applying the non-parametric linear programming DEA (Data Envelopment Analysis). The difference in the two methods lies in defining the efficient frontier (i.e. the most efficient firms in the sample), which must be obtained or estimated using the sample data. The SFA method, originally proposed by Aigner et al. (1977), involves the estimation of efficient production function and it assumes that any deviation from the frontier in Figure 1 is composed of two parts, one representing the randomness (or statistical noise) and the other inefficiency. The random error term reflects all events outside the control of the organisation, but also misspecification of the production function, or simply the measurement error. The main drawback of the SFA approach comes from the fact that it requires assumption of production technology which might be not known a priori.

On the other hand, the DEA method introduced by Charnes et al. (1978), based on the pioneering work of Farrell (1957), is a linear programming technique that constructs a non-parametric piecewise-linear convex frontier (in this case the production possibility curve) using the observations on the firms in the sample where the 'best' firms will define the efficient production. The DEA method in contrast to parametric SFA does not impose a specific functional form on the production technology of examined PA firms. Moreover, DEA can be easily extended to analyse the productivity of the PA firms, which is composed of both technical efficiency and scale efficiency (Banker et al. 1984). The main drawback of the conventional DEA method is that it implicitly assumes that all of the distance between an observed firm and the optimal frontier reflects inefficiency. However, the distance of an observation from the efficient boundary reflects both inefficiency and noise. This is because the observed input-output data could be subject to measurement error, or there could be noise in the data due to omitted input or output variables. In what follows, we will consider both methods to estimate TE and efficiency determinants of the Italian theatrical firms.

3.1 SFA production function

Estimating an output-oriented TE in the SFA framework requires a specification of a parametric functional form of the frontier using either a single-output production function or an output distance function in case of the multiple-output production technology. To estimate TE for the Italian PA firms, we use one output and two inputs production function model. The simplest and the most common functional form used in many SFA applications is the Cobb-Douglas production function. However, this functional form imposes certain restrictions on the production structure, such as non-varying returns to scale and unitary elasticity of substitution. Therefore, to account for the non-standard features of production associated with the performing arts, a flexible functional form is preferred and a translog (logarithmic transcendental) function by Christensen et al. (1973) is applied. Expressing output and inputs in natural log values, the translog stochastic production function can be written as:

$$\ln(Y_{it}) = \alpha + \beta_K \ln K_{it} + \beta_L \ln L_{it} + 0.5\left[\beta_{KK}(\ln K_{it})^2 + \beta_{LL}(\ln L_{it})^2\right] + \beta_{KL} \ln K_{it} \ln L_{it} + d_t + v_{it} - u_{it} \quad (1)$$

where Y_{it} is the real output (total revenues) of the i^{th} theatrical firm in year t ($i=1,2,\ldots,N$ and $t=1,2,\ldots T$), K_{it} and L_{it} are the capital (total assets) and labour (number of employees) inputs used in the artistic production. d_t is the dummy variable for each year that might cause the shift in the production function, v_{it} is the statistical noise term with zero mean and constant variance, and

$u_{it} \geq 0$ is a non-negative one-sided inefficiency term which follows a half-normal distribution so that $u_{it} \sim N^{+}\left(0, \sigma_u^2\right)$. The parameters of the model in Eq. (1) are estimated by maximum likelihood (ML) and the inefficiency term is computed using the technique of Jondrow et al. (1982), so that $E[-u_{it} \mid v_{it} - u_{it}]$. Furthermore, Aigner et al. (1977) parameterised the log-likelihood function for this half-normal model in terms of $\lambda^2 = \sigma_u^2 / \sigma_v^2$ and $\lambda^2 = \sigma_u^2 / \sigma_v^2 \geq 0$. If $\lambda = 0$, then there are no technical inefficiency effects and all deviations from the production frontier are due to noise.

Given that $u_{it} \geq 0$, observed output, y_{it}, is bounded below the frontier output (y_{it}^{*}). The latter is the maximum possible output defined by Eq. (1) above minus u_{it}. Hence, the term u_i is the log-difference between the maximum and the actual output ($u_i = lny_i^{*} - lny_i$), and it equals to u_i x 100% which is the percentage by which the actual output could be increased without increasing the inputs of production. From this follows that the technical efficiency index (TE_{it}) for firm i in year t is given by:

$$TE_{it} = \frac{y_{it}}{y_{it}^{*}} = \exp(-u_{it}) \tag{2}$$

As noted by Kumbhakar et al. (2014), the SFA estimates of technical efficiency often depend on model specification and distributional assumptions of the inefficiency term (u_{it}) and the exact exposition of the SFA method used will be explored in Section 5.

3.2. Output-oriented DEA

An output-oriented Data Envelopment Analysis (DEA) approach is also adopted in this study to compare the TE scores obtained in the parametric stochastic production frontier with the non-parametric approach. Following Färe et al. (1989), and Färe et al. (1994), we estimate an output-oriented technical efficiency (TE) under variable returns to scale technology (VRS) (Banker et al. 1984). Suppose, we have i theatres as decision making units (DMUs) in each time period t, then the linear programming model for obtaining TE score of the PA firm i for a given period t is:

$$\begin{aligned} &\text{Max}_{\square, \lambda}\ \phi \\ &\text{Subject to: } -\phi y_{it} + Y\lambda \geq 0 \\ &\qquad x_{it} - X\lambda \geq 0 \\ &\qquad I1'\lambda = 1 \\ &\qquad \lambda \geq 0 \end{aligned} \tag{3}$$

Where $1 \leq \phi \leq \infty$ is a proportional increase of output each i-th PA firm in year t should achieve to be considered as being output efficient (i.e. to be located on the frontier), with input quantities holding constant (Daraio and Simar 2007); λ is a $I \times 1$ vector of constants with $\lambda \geq 0$, x_{it} is the amount of the labour and capital input used by the DMU i in year t, y_i is the output produced by the i-th DMU in year t, and all input and output variables are measured as before.

When $\phi = 1$, then the current output level cannot be increased proportionally, indicating that this DMU *i* is on the DEA frontier (for example at point P in Figure 1). On the other hand, DMU is inefficient if $\phi \geq 1$ which means that the same input level can be used to reach more output than the current level and this corresponds to the ratio OP/OR in Figure 1 for firm operating at point R. The parameter ϕ is also the output distance function defined by Farell (1957) and its reciprocal defines the TE as before for the *i*th firm in year t:

$$TE_{it} = 1/\phi. \tag{4}$$

Furthermore, the convexity constraint $(I1'\lambda = 1)$ is added to the Eq. 3 above to account for variable returns to scale (VRS) DEA model according to Banker et al. (1984). Removing the constraint, the model reduces to constant returns to scale model (Charnes et al. 1978).

At last, to calculate the scale efficiencies, we compare the VRS and CRS TE scores of a DMU *i* in year *t*, if we detect a difference on two scores, then we can conclude that a PA firm is scale inefficient (Coelli et al. 2005). Thus, the gap between two scores implies the following equality:

$$TE_{it}^{CRS} = TE_{it}^{VRS} \times SE. \tag{5}$$

Figure 2 shows a graphical illustration of an output-oriented DEA model under VRS and CRS technology, with one single input and single output. We assume that firms can use different production technologies. A firm at point R is not only technically efficient but is also most produvtive as it is able to produce more output per unit of input, hence it is located on a CRS frontier. On the other hand, firms producing at points G and S are technically efficient as they lie on the VRS frontier but they are not scale efficient as their output per input is not the maximum possible which could be achieved if they produced on the CRS frontier. Finally, firm P is both technically and scale inefficient and it should at least produce at point P_v to be technically efficient or at point P_c in order to be fully productive. The TE score of a firm producing at point P is then equal to CP/PP_v when measured under VRS technology or to CP/PP_c when measured under CRS technology. The same firm's scale efficiency (SE) is then defined in the ratio form as CP_v/CP_c which is equal to TE^{crs}/TE^{vrs} according to Eq. (5) above. If this ratio is smaller than one, then the firm is scale inefficient. The presented DEA model will be further extended in Section 5 by using bootstrapping procedures to estimate both confidence intervals of the obtained TE and SE scores, and also to estimate the parameters of the efficiency determining variables.

3.3 Determinants of technical efficiency

A further aim of this work is to verify the impact of public subsidies on TE of performing arts companies controlling for firm' size, age, and firm's location, which in the Italian performing arts sector may be considered as factors affecting firm's performance. It should also be noted that the efficiency determinants are neither inputs nor outputs of a theatre but they might influence the distance from the production frontier, and hence they might affect technical efficiency as presented in Eq. (6):

$$TE_i = f(Subsidies_{it}, Size_{it}, Age_{it}, Area_i) \qquad (6)$$

where $Subsidies_{it}$ indicates the amount of public funds received by the firm, $Size_{it}$ is firm's size: *micro* if the firm has 0-9 employees, small if the firm has 10-49 employees, middle sized if the firm has 50-249 employees, and large if it has more than 250 employees; Age_{it} is the age of the firm in years; and $Area_i$, indicates the dummy variables for the four Italian macro territorial areas (*North_West*, *North_East*, *Centre*, and *South and Islands*).

Public subsidies were introduced in the performing arts sectors after the seminal paper of Baumol and Bowen (1965) on the cost disease afflicting this sector. Many governments introduced a law to sustain the performing arts. However, since the introduction of these subsidies, economists had different point of view on the overall influence of public subsidy on technical efficiency performing arts firms. Public funding may be correlated, for example, with higher expenditures on more talented artists that would turn in increasing quality and hence in the output of the firm. On the other side, the standard argument could also apply that public funding might have an adverse effect on the incentives of the theatre management and the employees to be efficient (see Bishop and Brand, 2003).

In the economic literature, firm performance is also depending on firm size that may affect its efficiency. However, this relationship is not well acquainted since empirical evidence suggests mixed results with regard to the link between efficiency and firm size in either direction. Diaz and Sanchez (2008) assert that whilst a positive effect may be expected due to the economies of scale, the firm size may be negatively linked to efficiency if large firms experience management and supervision problems. On the other side, Jha et al. (1998) find that large firm size is associated with higher technical as well as allocative efficiency. These mixed results may be influenced by technology and sector characteristics. However, since we are analysing a sector where the technological progress is scarce and the Italian performing arts sector is largely composed of small and medium theatres, we expect that the efficiency of theatrical sector is positively influenced by small and medium size.

We also test whether older firms are more efficient than younger ones. According to Castiglione (2012) a positive relationship between age and TE can be expected due to 'learning by doing' which occurs through production experience. Over time, firms become more efficient as a result of a growing stock of experience in the production process. However, other economists argue that when an innovation is introduced, older firms may have to delay adoption as it may be too costly to substitute old methods, thus implying that efficiency may decrease with age. At the Italian level, Castiglione and Infante (2014) find a positive effect of age on firm efficiency for the manufacturing sector.

To examine the effect of the subsidies and other environmental variables, we extend both the parametric SFA model and the non-parametric DEA introduced earlier to estimate not only TE but also the parameters of efficiency determinants in a single-stage procedure. Many previous studies examined the effect of environmental variables by employing a two-stage approach wherein parametric or non-parametric efficiency estimates from the first stage are regressed on a vector of other variables in a parametric analysis. However, according to Badunenko et al. (2015), Kumbakhar and Lovell (2014) and Simar and Wilson (2011), whatever the second-stage regression technique employed, conventional inference methods fail to give valid inference due to the fact that in the second-stage, true efficiency remains unobserved and must be replaced with estimates of efficiency, and these are serially correlated by construction. Hence, using the point estimates of TE in a second stage analysis may cause biased and inconsistent estimates of the parameters of the efficiency determining variables. Following this, in this research both parametric and semi-parametric procedures are explored that properly integrate the effects of efficiency determinants as explanatory variables and these aproaches will be discussed in Section 5.

4. Data

To estimate the (in)efficiency of the Italian theatre, we use an unbalanced panel of 168 Italian firms for the period of 2006–2014. The data were collected from two sources: the *Analisi Informatizzata delle Aziende* - Computerized Analysis of Firms (AIDA), and from the *Ministero dei Beni delle Attività Culturali e del Turismo* (MiBACT) (2014).

The AIDA database is carried out by Bureau van Dijk and contains detailed accounts following the scheme of the 4th Directive EEL, indicators and trade description of Italian companies, divided by economic sector and geographical area. Other information includes year of incorporation, ownership and number of employees. After matching the data from the AIDA and MiBACT we obtained a 168 theatres, for a total of 1512 observations, belonging to the following categories: Lyric-Symphonic Foundation, Theatre of Tradition, Lyrics, Permanent Public Theatres, Permanent Private Theatres, Permanent Innovative Theatres, Theatre Companies.

Information on output, inputs and other firm-level characteristics are from the AIDA dataset. The number of performing arts firms with non-missing values for output and inputs and non-zero turnover, amounted to 148 firms, which forms an unbalanced panel data with 723 observations. Output (*Y*) is measured by the amount of revenues from sales and services at the end of the year; labour input (*L*) is measured as the total number of employees at the end of the year; and capital stock (*K*) in a given year is proxied by the nominal value of total fixed assets which includes both tangible and intangible assets. Both output and capital stock were deflated using Consumer Price Index (CPI) published by ISTAT (2015).

Data on the public subsides are taken from the annual report on the Fund for the Performing Arts (FUS) for the years 2006-2014. We have choosen from this relationship the firms that are subject to present the balance sheet data, and hence are present also in the AIDA database.

According to the MiBACT Annual Report (2014) the FUS (at 1985 constant values) has decreased continuously from an initial allocation of €357,480,000 at its start in 1985 to a recent all time low of €162,510,000 in 2014, representing an overall decrease of 55% since the fund was created (Figure 3). In 2014, the FUS allocation was divided in varying proportions between the different performing arts and cinema activities. Given the centuries-old Italian tradition of "bel canto", the Opera Foundations received 45.6% of the 2014 FUS budget, followed by cinema (20.7%), music (14%), dance (2.6%) and circus (1.3%). Theatre and drama activities received 15.7% of the total annual allocation (Figure 4). The FUS contributions to theatres and companies are allocated according to quantitative (mainly production and running costs) and qualitative (mainly multiannual activity, artistic direction, innovation) criteria. To receive a contribution from the FUS, an Italian performing arts company must present a final report on the work performed, independent of box office revenues and spectator numbers.

Table 1 includes definitions of all variables and sources of data, whilst Tables 2 provides the sample summary statistics of the variables used in the analysis. According to Table 2, there is a considerable variation in output and inputs about their means. The efficiency determinants which are continuous variables and affect the variability and hence the mean of the inefficiency are also presented in Table 2. The average *Age* of the firm is about 21 years with zero being the minimum age. The *size_1* variable indicates that the very small theatres with less than 10 employees account for 20% of the observations in our sample, whilst the small firms (10-49 employees, *size_2*) account for more than half of the observations in our sample (65%), followed by the middle-sized firms (*Size_3* which is 50 to 249 employees) and by only 6% of companies, finally large companies, with more than 250 employees, account for 9.4%. Finally, the area in which the theatre companies are located as the population are roughly equally distributed among the four large different regions in Italy.

5. Estimation strategy

To estimate the technical efficiency of the Italian theatres, we apply both the parametric SFA framework and the non-parametric DEA method as introduced earlier as these are the two most relevant approaches to measure efficiency and efficiency determinants. While earlier section presented the basic exposition of the two methods, in this part of the paper we formulate the extensions of the two methods to estimate both robust TE scores and unbiased parameters of the efficiency determining variables for the PA sector in Italy.

5.1. The SFA model for PA firms

The main drawback of SFA production function model of Aigner et al. (1977) defined in Eq. (6) is that it does not control for any omitted variable biases. The omission of firm's heterogeneity is particularly relevant for the PA sector and it may lead to biased estimates of the parameters describing the production frontier and to an understatement of technical efficiency (Zieba 2011, Castiglione et al. 2017). To adjust for this drawback in the original model, we apply an extension of the stochastic production frontier defined in Eq. (1) which is a panel data SFA model of Greene (2004, 2005). Greene proposes a 'true-random effects' (TRE) approach that integrates into original SFA model, the firm-specific random component (w_i) that is not related to the (in)efficiency but to the unobserved heterogeneity of the firms. Assuming the translog production function specified in Eq. (1), the TRE SFA panel data model can be written as:

$$\ln y_{it} = w_i + d_t + g_f + f(x_{it};\beta) + v_{it} - u_{it} \tag{7}$$

where $\ln y_{it}$ is the log of observed output (revenue) for firm i in year t, and x_{it} is the vector of inputs (in logs); β is a $J\ x\ 1$ vector of the corresponding production function parameters, including the constant that is common to all firms. As regards the model parameters, v_{it} is the statistical noise term with zero mean and constant variance, $u_{it} \sim N^+(0, \sigma_u^2)$ is a non-negative stochastic term representing inefficiency of firm i in year t; and $w_i \sim N^+(0, \sigma_\alpha^2)$ represents a time-invariant, firm-specific random intercept which captures the unobserved individual firm's heterogeneity. Furthermore, g_f are the indicator variables for the three groups of the Italian PA firms: operas (g_1), companies (g_2) and theatres (g_3), and d_t are the time-fixed effects. Both v_{it} and u_{it} can be expressed as a two-part composite error that is: $\varepsilon_{it} = v_{it} - u_{it}$ which is not normally distributed.

For the TRE SFA model the inefficiency term, u_{it}, is computed as the simulated conditional expectation of inefficiency which is $E[-u_{it} \mid w_i+\varepsilon_{it}]$ whereas w_i is integrated out of u_{it} using simulations presented in Greene (2005, p. 290). Consequently, following Eq. (2) presented in Section 3, the term u_{it} is the log-difference between the maximum output ($\ln y_{it} = w_i + d_t + f(x_{it};\beta) + v_{it}$) and the actual observed output (lny_{it}).

Due to the inclusion of unobserved heterogeneity term, w_i, the TRE model presented in Eq. (7) has important advantages as it differentiates between unobserved time-varying efficiency and exogenous heterogeneity of firms through random effects (Farsi et al. 2006). Moreover, as highlighted in Eq. (7), we use dummy variables to control for different production technologies of the main three firm groups (g_f). The inefficiency of firms is also time-varying which is an appropriate assumption given the fact it is a dynamic phenomenon (Farsi et al., 2006). This holds especially for our analysis as the number of time periods in the panel is large, and thus, it is difficult to assume a persistent level of inefficiency. Furthermore, the TRE SFA model in contrast to the time-invariant efficiency panel data models (e.g. Pit and Lee 1981), it controls for omitted variable biases in the production function coefficients and in the estimates of technical (in)efficiency.

It should be noted that the TRE model provides unbiased estimates of the production functions parameters under the assumption of no correlation between firm-specific random components (w_i) and the explanatory variables (inputs). Thus, in line with Farsi et al. (2005), Pieri and Zaninotto (2013), we account for this possible correlation. We apply adjustment by Mundlak (1978) which is a simple modification for the TRE model. We call this model TREM specification which involves inserting the within-group means of inputs in the production frontier model which is given in an auxiliary regression of the form:

$$w_i = \lambda' \cdot \overline{X_i} + \eta_i \tag{8}$$

where $\overline{X_i} = (1/T_i)\sum_{t=1}^{T} X_{it}$ are firm specific means, T_i is the number of time periods for firm i, λ' is the corresponding vector of coefficients to be estimated, and $\eta_i \sim N(0, \sigma_\eta^2)$. Eq. (8) divides the firm-specific stochastic term into two components: the first explains the relationship between the exogenous variables and the firm-specific effect (with the auxiliary coefficients λ_i) and the second component, η_i, is orthogonal to the explanatory variables. In this way we control for any correlation between the exogenous variables and the heterogeneity component eliminating any bias.

Moreover, we can integrate the effects of efficiency determinants as explanatory variables in estimating the true unbiased technical efficiencies, by incorporating them either in the estimated distribution of inefficiency or directly in the production function. According to Greene (2004), there is no clearly defined rule which indicates how these factors should enter the model. In this research, we extend the TRE and TREM models, presented above to allow for heteroscedasticity in the one-sided technical inefficiency error component. Following Caudill et al. (1995), Hadri (1999), Wang (2002), Hadri et al. (2003), and Greene (2007) we include the efficiency determinants Z_k as heteroscedastic variables in the inefficiency function, directly parameterising the variance of the inefficiency:

$$\sigma_{u_{it}}^2 = \exp(\delta' Z_{it}) \tag{9}$$

where Z_{it} is a vector of variables defined earlier in Eq. (6) which influence the inefficiency of performing arts firm *i* in year *t* and δ is a vector of unknown parameters to be estimated. Unlike the classic linear model in which heteroscedasticity affects only the efficiency of the estimators and not their consistency, ignoring the observed heteroscedasticity in u_{it} may lead to biased estimates of both TE and the production function parameters (Kumbhakar and Lovell 2000; Kumbhakar et al. 2014). It should also be noted that other studies (e.g. Wang 2002; Diaz and Sanches 2008) include the inefficiency factors in line with Battese and Coelli's (1995) method, that is directly in the mean of the inefficiency function where u_{it} is assumed to be independently distributed as truncations at zero of the $N(-Z_{it}\delta, \sigma_u^2)$ distribution. However, this approach becomes highly unstable in practice within the true-random effects model framework, and it is not applied for our data due to its complexity and issues with the convergence (see e.g. Pieri and Zaninotto 2013). In contrast, we treat the efficiency determinants as heteroscedastic variables of the inefficiency term as explained above. As noticed by Greene (2007), allowing variance of inefficiency to vary over individuals and/or time induces not only the heteroscedasticity but also the variation in the mean of u_{it}.

5.2. The double-bootstrap DEA model

We apply the two-stage double (semi-parametric) bootstrap DEA method to first, address the main drawback of the conventional DEA approach which does not account for random errors. The bootstrapping in DEA was developed by Simar and Wilson (1998, 2000). This procedure incorporates sampling repeatedly from the obtained CRS and VRS DEA efficiency scores described in Eq. (3), and constructing an empirical sampling distribution for the DEA TE efficiencies of the PA firms. The bias in the DEA efficiencies can then be estimated and 95% confidence intervals can be built using this empirical distribution.[1] Second, the double bootstrap (DB) DEA procedure in line of Simar and Wilson (2007, 2011) allows us to obtain unbiased estimates of the parameters of our posited determining variables and additionally to get bias-corrected bootstrap TE scores which are adjusted by the values of the efficiency determining variables.

To perform the DB DEA, we adopt Algorithm 2 set out by Simar and Wilson (2007). The Simar and Wilson's (2007) algorithm is performed in the following stages.[2] Firstly, we run in each case the truncated regression where the reciprocals of our original DEA TE scores for each nursing home *i* are regressed on the vector of environmental variables. The truncated regression is run twice. The first stage of the truncated regression model is given by the following equation:

[1] It should be noted that the method developed by Simar and Wilson (2000) is relatively robust to the chosen bandwidth of the confidence intervals.
[2] The estimations are performed in R using the rDEA package in line of Simm and Besstremyannaya (2015).

$$\phi = 1/TE_{it} = f(Subsidies_{it}, Size_{it}, Age_{it}, Area_i) \quad (10)$$

where TE_i is the technical efficiency and the explanatory variables are efficiency determinants described in the previous section. Computations are done in terms of the Farell's (1970) output distance function which was defined in Eq. (3) and which is the reciprocal of technical efficiency score (TE). Hence, ϕ ranges from one (indicating a full technical efficiency) to infinity (indicating full inefficiency). After obtaining the results from the truncated regression model given by Eq. (10), we apply a bootstrapping procedure to correct for bias problem in original DEA scores. The bootstrap steps are as follows. First, we obtain empirical distributions by taking L1=100 drawings of residuals from a truncated normal distribution. The truncated regression model is then re-estimated for each drawing to estimate the bias-corrected reciprocals of TE scores. Furthermore, we obtain the DEA TE scores by adjusting the input values for the ratio of original DEA TE estimates to bias-corrected DEA TE scores.

In the second stage of truncated regression model, we re-run the truncated regression model – this time with the bias-corrected reciprocals of efficiency scores, $1/TE^*$, as the dependent variable and with the explanatory variables as given in Eq. (10). The second stage is presented in Eq. (11):

$$1/TE^*_{it} = f(Subsidies_{it}, Size_{it}, Age_{it}, Area_i) \quad (11)$$

In the second truncated model given by Eq. (11), we take L=2000 drawings of residuals from a truncated normal distribution. The truncated regression model is re-estimated for each drawing. Following this, we obtain a set of robust coefficients of environmental variables in the truncated regression of the reciprocal of TE* score on environmental variables (i.e. after the second loop). The lower and upper bounds for β-coefficients are also obtained. The robust DB CRS and VRS TE scores are further used to derive robust scale efficiency (SE) scores according to the definition of scale efficiency.

As DB DEA method does not impose any restrictions on the functional form of the production technology, as in the case of SFA specification, we can estimate the efficiency factors and determinants for smaller sample sizes. Thus, we estimate the DB DEA model for the whole sample but also for the different groups of PA firms (operas, companies and theatres), separately. Moreover, the DB DEA model applied in this study uses pooled data for different years in the so-called pooled or panel DEA model to gain greater consistency in the DEA results. With this procedure, theatres in different years are treated as if they were different DMUs. This approach allows us to compare the efficiency of a DMU with its own efficiency in other years, as well as with the other DMUs' efficiency (Herrero-Prieto and Gómez-Vega 2017). Consequently, we also have a dynamic evaluation of PA firms performance over time which can be compared with the SFA model for the full sample. Nevertheless, using panel DB

DEA model it is impossible to control for noise but also for the unobserved heteregeneity of the PA firms as in the SFA panel data model presented earlier, and this might have consequences for over- or underestimating the the true TE scores.

6. Empirical results

6.1. SFA estimates

6.1.1. Production function estimates and TE scores

The SFA estimates are presented in Table 3 using both the true-random effects (TRE) model and the true-random effects model with Mundlak adjustment (TREM).[3] The results are presented for the full sample of all PA firms and we control for each firm group by using the indicator variables (g_f) in the production function as indicated by Eq. (7) above.[4] Accordingly, we assume that the production function intercept will change for the three different groups of the PA firms. Columns (1) and (3) present the results including dummy variables for operas (g_1) and companies (g_2) while theatres (g_3) are the base category. To confirm the robustness of our results, columns (2) and (5) present the results including dummy variables for PA companies (g_2) and theatres (g_3) and using operas (g_1) as the reference category. Furthermore, columns (3) and (6) in Table 3 present the 'homogenous production functions' that exclude the individual group dummies for the three groups of PA firms. All the models presented in Table 3 include also the coefficients of the efficiency determinants that are in detail discussed in the next section.

The Hausman test rejects in all cases the hypothesis of no correlation between the inputs and the firm-specific characteristics (w_i) which suggests that the true-random effects specification with the Mundlak's adjustment (TREM) gives unbiased production function coefficients and so it is the most appropriate model. Nevertheless, the magnitudes of the production function parameters are very similar across the two specifications in Table 3, and hence both models are presented.

As all inputs and output variables are normalised at their sample mean prior to the estimation of the translog production function, the presented first-order coefficients (β_1 and β_2) are directly interpreted as output elasticities with respect to labour and capital, respectively. The estimated output elasticities are positive and significant at the 1% level. The total share of the statistically significant translog production function coefficients is also reasonable. Consequently, the estimates provide large enough well-behaved regions of the approximated underlying production technology. Moreover, the output elasticity of capital is much higher

[3] All models were estimated using LIMDEP version 3.0 (Greene 2007).

[4] Due to small size sample for the separate firm groups, the ML functions did not converge or had the wrong skewness when the subsamples for the different PA firm groups were used separately. This confirms the restrictions of the parametric SFA methods. This issue, in particular, was valid for operas and theatres. While some model specifications could be estimated for the firm group 'companies', these results were very similar to those found in Table 4 for the whole sample.

than that of labour, suggesting that the largest contribution to the production in the theatrical sector in Italy is due to capital input. This result can be explained by the fact that the output per man-hour cannot be easily raised in the performing arts sector and the productivity improvements may arise from increases in capital rather than in labour, such as capacity of venues, organisation, directing, rehearsing, scenes and costumes.

Furthermore, the total elasticity of scale, or total output elasticity, which is defined as a local measure of returns to scale, ranges between 0.88 and 0.89 for all model specifications in Table 3, except for column (3) which displays the returns to scale of 0.66 for the TRE model without the firm group dummies. Based on the most appropriate TREM model specification (columns 4-6), which controls for the correlation of firm-specific effects with production function coefficients, we can conclude that the returns to scale are around 0.88 but smaller than 1. Thus, at the sample mean, the decreasing returns to scale (DRS) are prevalent in the Italian performing arts sector, indicating that increasing all inputs by 1% output would increase by less than 1%. The evidence of decreasing returns to scale in the Italian performing arts sector was also found in Castiglione et al. (2016) for performing arts sector in Italy albeit using a different and a smaller data set. Similar result was also found in the previous studies on theatres such as Zieba and Newman (2013) for German theatres, and Zieba (2011) for Austrian and Swiss theatres, and Gapinski (1980; 1984) for the performing arts firms in the UK and the US.

Table 3 displays also the yearly dummy variables, d_t, with year 2006 being the reference category. They represent the time-varying effects in production function that are constant for all firms but change over time. Hence, they can be interpreted as technological change and they are statistically significant and negative in particular for the years 2009 to 2014. This finding is also reinforced when following Coelli et al. (2005), we substitute the time dummies with the simple time trend and the trend squared. The time trend is always significantly smaller than zero and the time squared is positive and significant as expected.[5] Overall, these results confirm our hypothesis that the technological progress is not present for the Italian PA sector during the examined period. The findings rather imply that the technological change is negative confirming the presence of Baumol's disease in this sector.

Summary statistics of the estimated average TE scores, the log-likelihoods and the variance parameters for the compound error (λ) are also presented in Table 3. The TE scores are very robust to the particular type of econometric specification and they are on average 0.74. The results imply that the Italian performing arts firms could increase output by 36% on average without increasing the inputs levels. These results are very similar to those obtained by Castiglione et al. (2016) who found the average TE scores of 0.68 for the Italian performing arts firms, albeit for different and smaller sample, and also for the different time period. Moreover,

[5] These additional results are available on request.

even if the theatrical firm sample tested in the present study is different from those used in other studies conducted for other countries, here we want cautiously compare the efficiency scores obtained in our research with the other efficiency studies. The average TE scores for Italian performing arts are lower than those found by Zieba (2011) for Austrian theatres (0.87) but similar for Swiss theatres (0.73). The TE scores are also much lower than those found by Last and Wetzel (2010) for German public theatres for the period 1991-2005 (which ranged between 0.967 and 0.964), and are also lower than those found by Zieba and Newman (2013) for German public theatres over the period 1972-2004 (which were about 0.85 on average). The TE scores found for Italian performing arts sector are higher than those found by Marco-Serrano (2006) for Spanish theatres which range between 0.24 and 0.54.

6.1.2 Estimates of efficiency determinants (Z_k)

The TRE and TREM models presented in Table 3, also report the estimated coefficients of the efficiency factors (Z_k) which are included as heteroscedastic variables in the inefficiency function as defined by Eq. (3). The estimated coefficients of the efficiency variables show their direct effect on inefficiency (u_{it}) which is the opposite effect on technical efficiency (TE).

The level of public subsidies which is our main variable of interest has a significant but negative effect on inefficiency, indicating a positive effect on technical efficiency. The coefficient is significant at the 1% level for the TRE model and significant at the 10% level for the TREM specification. The positive effect of subsidies on technical efficiency is in line with the findings obtained in Zieba (2011) for the Austrian and Swiss theatres. One explanation for these results might be that the public funding increases the incentives of firm managers to spend more on intangible inputs in order to improve quality which in turn increases the output of the firm. Public funding may be correlated, for example, with higher expenditures on more qualified or more talented staff members or renovation which would in turn increase quality and hence the output of the firm by the given level of inputs. This finding is in contrast to the results obtained by Bishop and Brand (2003) for public museums although a slightly different variable was used in the latter study.

The estimated coefficients of efficiency determinants are very similar for both the TRE and TREM models presented in both tables. The results with regard to the size variable indicate that *size_2*, which denotes 10-49 employees, has always a significant and negative effect on inefficiency (u_{it}). This implies that the small-sized firms are more technically efficient than the micro firms with less than 10 employees, the latter being the reference category (*size_1*). Thus, the small-sized firms could be considered as those with the most-efficient size for the theatre market in Italy, given that medium-sized firms (*size_3*) do not present any statistical difference from *size_1* firms, whilst large firms (*size_4*) present significant higher inefficiency than the reference category (*size_1*) in all specifications. This result demonstrates that the Italian theatre companies could significantly increase their technical efficiency by moving to the small scale represented by firms that operate with 10-49 employees, thereby removing scale inefficiency.

The age_{it} of the firm should have a positive effect on TE and hence a negative effect on inefficiency. Our results confirm this hypothesis as the age of the firm contributes significantly to changes in inefficiency for the Italian arts companies. For both the TRE and TREM models, the age coefficient is significant and negative, implying that it has a positive effect on technical efficiency.

As regards the regional differences, we found that theatres located in the North-West and North-East of Italy, have significantly higher efficiency scores in contrast to the companies located in the South and in the Centre of Italy, the latter being the reference category. According to Figure 5, theatrical firms which are included in our sample and are located in the Central area of the country (where the Lazio region is situated), received the smallest amount of public funds per firm over the examined time period. In contrast, firms located in the North of the country (North-West and North-East regions), received the highest amount of public funding. This descriptive statistics reinforces our earlier finding that subsidies have a positive effect on technical efficiency. From this also follows that firms located in the Northern part of Italy might increase technical efficiency due to higher public funds availability.

We also include the type of the firm (operas, companies or theatres) as the variables not only affecting the production technology but also the variance of inefficiency. However, we do not find significant effects on the technical (in)efficiency scores (not reported in the table). Hence, we conclude that the differences in the TE scores between the PA firms groups are explained by important differences in production function (technology) between the theatrical firm groups only.

Moreover, the significant and positive effects of subsidies on TE scores coincide with the findings related to the technological progress for Italian PA firms. From Figure 6, there was a decrease in the amount of average level of public subsidies per theatrical firm in the more recent years and this also corresponds with the negative and significant time dummy coefficients obtained for the years 2009-2014 in Table 3. Hence, one of the reasons for the negative technological change and hence the decreasing productivity of Italian PA firms might be the decreasing level of public funding. Moreover, Figure 7 also highlights the fact that the years with the higher average TE scores for PA firms correspond with higher level of public subsidies.

6.1.3. SFA specification tests

In order to check the robustness of the SFA model, we applied generalised likelihood ratio (LR) tests for all SFA techniques used. Firstly, we test the presence of inefficiency term (u_{it}) in the model and the test is based on the log-likelihood values of the OLS (the restricted model which can be obtained by excluding u_{it} from Eq. (1)) and the stochastic frontier models (TRE and TREM models presented in Table 3). We reject the null hypothesis of no one-sided inefficiency term in all cases, thus confirming that applying the average response function with just the error term, v_{it}, is not adequate to our data. Secondly, we test the alternative Cobb-Douglas (C-D) production function (the restricted model) against the translog production function (the unrestricted model), and the null hypothesis of $\beta_{LL} = \beta_{KK} = \beta_{LK} = 0$ is always rejected at the 1% level of significance confirming that the flexible translog function fits our data better.

We also test the restriction that the effects of efficiency determinants are jointly zero (see also Battese and Coelli 1995). The null hypothesis that the variance of inefficiency is not a function of those factors is rejected at the 1% level of significance. This implies that the SFA models which include the Z_k-variables as explanatory factors provide a better fit to the sample data than the basic SFA specification. As a result, the presented TRE and TREM models with heteroscedastic inefficiency term are an important extension of our analysis as they not only explain possible sources of inefficiency but also incorporate both the observed and unobserved heterogeneity of performing arts companies. Finally, we also tested the restricted TRE model against the unrestricted TREM model. The LR test strongly rejects the null hypothesis that the Mundlak terms are jointly not significant (H_0: $\lambda_1= \lambda_2= \lambda_3= \lambda_4= \lambda_5=0$) in the TREM model, concluding that this model is the most appropriate SFA specification.

6.2 Double bootstrap DEA results

The semi-parametric double bootstrap DEA model results are presented in Table 4. The table presents the actual technical efficiency (TE) scores, the scale efficiency (SE) scores and the estimated coefficients of the efficiency determinants. The lower and upped bounds (obtained after the bootstrapping) of the estimated parameters of the efficiency factors, and of the TE and SE scores are also presented. Moreover, as the DEA analysis does not require specification of the functional form of production technology, it is possible to use separate frontiers for the three different firm categories (g_f). Therefore, in Table 4 we can present results for all PA firms and also for the separate samples: 'operas', 'companies' and 'theatres'.

At first, we can find that the obtained TE scores are very low in comparison to those obtained using the SFA model above. The average TE score for all firms is 0.25 and implies that firms output should be increased by 75 percent on average without increasing the inputs levels. Moreover, there are slight differences in the obtained TE scores for the different sectors of PA firms. The companies (g_2) which constitute the greatest sample with 105 firms and 474 observations, have an average TE score of 0.25, which is lower than the average TE scores found for operas (0.316) and theatres (0.304).

The summary statistics of TE scores for all firms and then for the different subsamples, obtained in both SFA (Table 3) and DB DEA (Table 4) models are presented in Table 5. Based on the theoretical discussion in the earlier section, we conclude that the TE scores are underestimated in the DB DEA model as the latter method does not account for noise or unobserved heterogeneity in our data set. However, the average TE scores are relatively lower for ‘Companies’ than for ‘Operas’ or ‘Theatres’ for all model specifications. ‘Operas’ are the most efficient PA firms. Moreover, the TE results obtained in DB DEA model are robust with regard to the firm’s technical efficiency rankings. Table 6 presents the correlation matrix of TE scores obtained for the various SFA models and of the TE score obtained for the whole sample in the DB DEA model. In fact, the correlation coefficient between the SFA TE scores and the DB DEA TE score ranges between 70 and 79 percent, indicating that the firm’s rankings with regard to TE between the two different methods are very close. This implies that an inefficient firm *i* in year *t* in the SFA model have a similar rank status in the DB DEA model.

Following these results, we argue that despite the fact that DB DEA method is underestimating the TE scores on average, it is a useful extension of our analysis. In contrast to the SFA model presented in Table 3, this method allows for estimating separate frontiers for the different groups of PA firms and disentangle the impact of efficiency determinants on TE scores of the different firm category. As can be found from Table 4, the effect of subsidies on technical efficiency varies between the different types of firms. For the whole sample and the ‘companies’ (g_2) the effect of subsidies has a positive and significant effect on TE as it was in the case of SFA model which was estimated for the pooled sample of all firms and was presented in Table 3. On the other hand, the effect of subsidies is negative and significant for operas (g_1) at the 1% level and also for theatres (g_3) but at the 10% level, only. This coincides with the fact that the ‘companies’ are on average less technically efficient than ‘operas’ according to Tables 4 and 5.

Moreover, the medium (50-249 employees) and small size (10-49 employees) have a significant and positive effect on TE scores for both ‘companies’ and ‘operas’, implying that the micro firms (0-9 employees) should increase and the large firms (250 and more employees) should decrease their scale of operations, respectively. On the other hand, in relation to theatres, the small and medium-sized firms are less technically efficient than the micro firms.

The effects of firms regional localization on the obtained TE scores are more consistent for the different sectors of PA firms and generally indicate that PA firms located in the South Islands (but also in the North-East for Companies) are less efficient than firms localized in other regions. This finding is also compatible with the SFA results which found that the PA firms in the northern regions of Italy are more efficient than those localised in the South or Centre part of Italy. However, in contrast to the results found in the SFA model, the age variable is always significant and positive indicating that with age the firm decreases TE. Hence, given the contrary results for the age variable in parametric and non-parametric specifications, we treat the findings about the age variable as not conclusive.

Finally, Table 4 also reports the scale efficiency scores for the Italian PA firms. The average SE score for all firms is 0.85 indicating that the firms are scale inefficient as confirmed by the decreasing returns to scale found for the parametric SFA model in Table 3. This finding also coincides with the significant effect of the size variable on technical efficiency for both the SFA model (Table 3) and the DB DEA model (Table 4). However, when considering the different sectors, the scale efficiencies for different subsample of PA firms are much higher than for the full sample. Although they are still inefficient (less than 1), they are almost one for 'Companies' and 0.95 for 'Operas' and 'Theatres'. This finding again confirms that the firm theatrical sectors have different production technologies and hence their scale efficiencies and overall productivities can vary depending on the sample size.

6.3 Summary of findings

Based on the fact, that the SFA model controls both for technical inefficiency component and the noise, we conclude that these estimates should be mainly used to derive the findings about the estimated TE efficiency scores for the Italian PA firms. Nevertheless, the DB DEA results confirm that the effect of subsidies can change depending on the group of PA firms examined. Whereas the subsidies increase TE for companies (g_2) they have a negative effect for operas (g_1) and theatres (g_3). This finding coincides with the fact that the 'Companies' are less efficient PA firms in the sample based on both parametric and semi-parametric results.

7. Conclusions

This work greatly contributes to the literature on the determinants of efficiency in the cultural sector. It adds to that strand by investigating the determinants of technical efficiency in the Italian theatrical firms, using their balance sheet data for the period 2006-2014.

To this aim we used both parametric SFA and non-parametric DEA approaches. Firstly, we estimated a translog stochastic production frontier and explored different panel data SFA models. We applied the TRE and TREM models to our data and found that the theatrical firms are very heterogenous. Secondly, we applied the two stage double (semi-parametric) bootstrap DEA method.

Our results confirm that controlling for both unobserved and observed heterogeneity in the SFA framework is crucial in order to get meaningful and realistic estimates of TE scores. Furthermore, our findings imply that whilst all inputs elasticities turn to be positive, decreasing returns to scale are prevalent in the Italian theatrical sector confirming that the performing arts face potential barriers of output expansion. More importantly, we provide robust estimates of the TE scores for the performing arts companies. These are considerably low and equal around 70%, implying that the performing arts firms could increase their output by around 30% using the same level of inputs. These results are also confirmed when we use the DB DEA method even though the TE scores are underestimated using this approach. However, the DB DEA method allowed us to estimate separate frontiers for different theatrical sectors to disentangle the impact of efficiency determinants on TE scores in these different theatrical sectors. Although the much lower TE scores registered using this approach, we have found that the in(efficiency) for categories and firm size is similar ranked using both SFA and DEA methods. This implies that an inefficient firm i in year t in the SFA model will have a similar rank status in the DB DEA model.

These findings are compatible with other efficiency studies for the performing arts sector (Zieba 2011; Zieba and Newman 2013; Castiglione et al. 2016). Our results also confirm that technological progress is not present for the theatrical Italian sector during the examined time period and hence they provide support for confirming the presence of Baumol's disease in this sector.

The main contribution of this paper, however, lies in investigating the impact of the public subsidies and other contextual factors on TE scores. We have found that public subsidies increase the efficiency of the Italian firms operating in the theatrical sector. Moreover, our empirical analysis suggests that theatres located in the Northern part of Italy might increase technical efficiency due to higher public funding availability. We have also found that small firms are more technically efficient than the others, confirming that in the Italian performing arts sectors the efficiency can increase incentivising the theatrical companies by moving to the small scale.

Turning to policy implications, our findings imply that policymakers should engage with performance measurement before allocating limited financial resources to the performing arts sector. This is a finding that corroborates results obtained for the performing arts sector in other countries.

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Figure 1: Definition of output-oriented technical efficiency (TE).

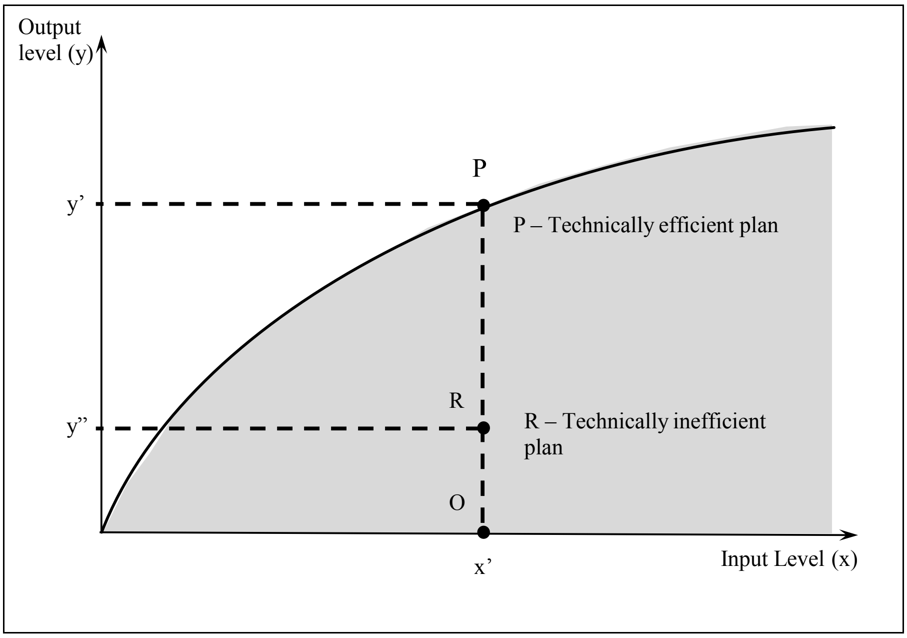


Figure 2: CRS and VRS technology in an output-oriented DEA.

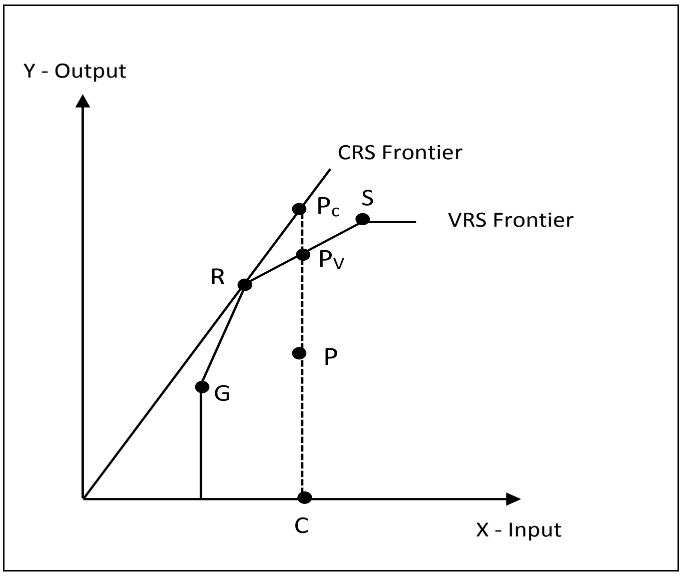
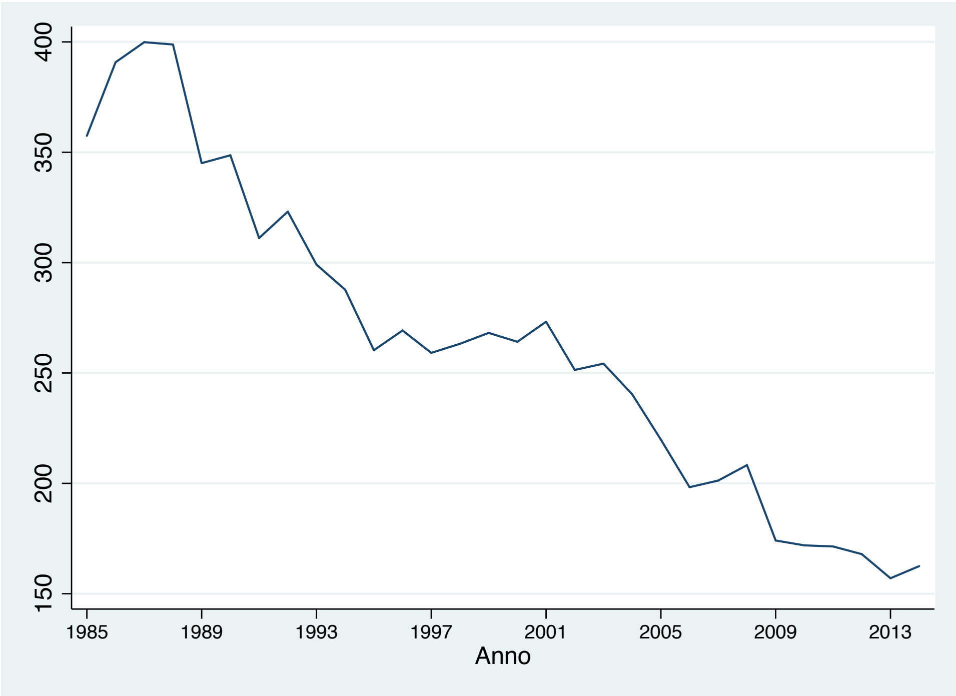
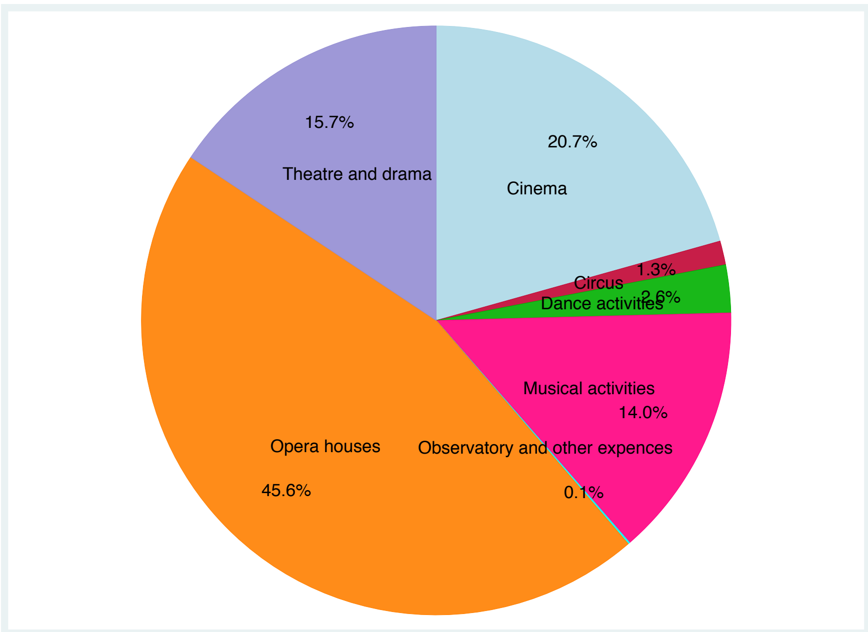


Figure 3: FUS annual allocation, 1985-2014, constant price 1985



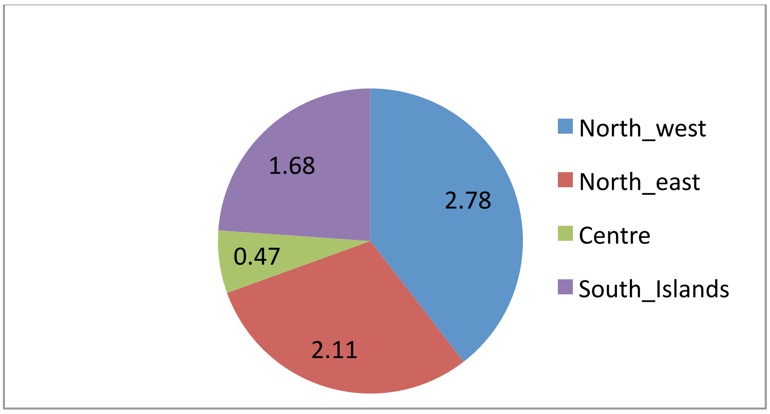
Source: Our elaboration on MiBACT (2014) data

Figure 4: FUS allocation by activities, 2014



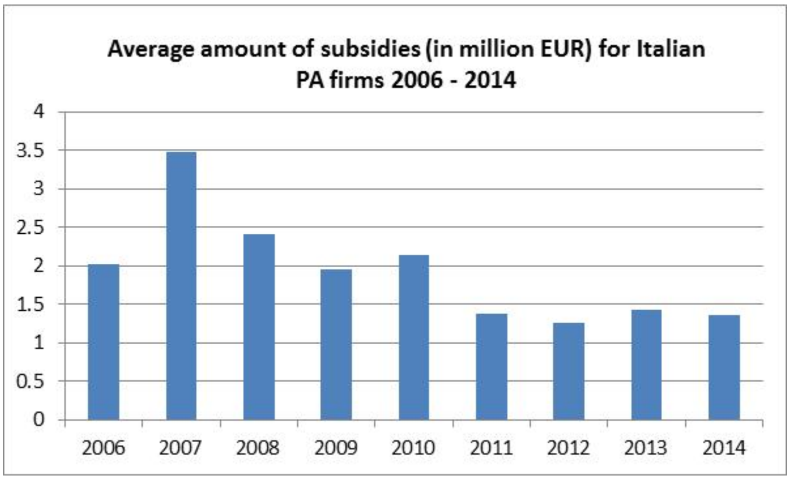
Source: Our elaboration on MiBACT (2014) data

Figure 5: Average amount of public subsidies (in million EUR) for Italian PA firms, by regions.



Source: AIDA database 2006-2014

Figure 6: Average public subsidies for the Italian PA firms over time



Source: AIDA database 2006-2014

Figure 7: TE scores for Italian PA firms over time

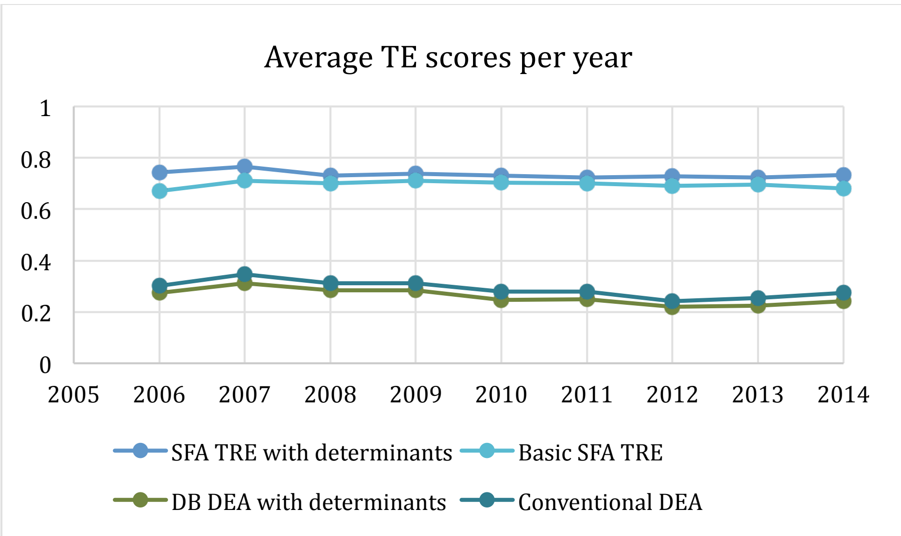


Figure 8: Kernel density functions for TE scores obtained for the SFA and DEA models.

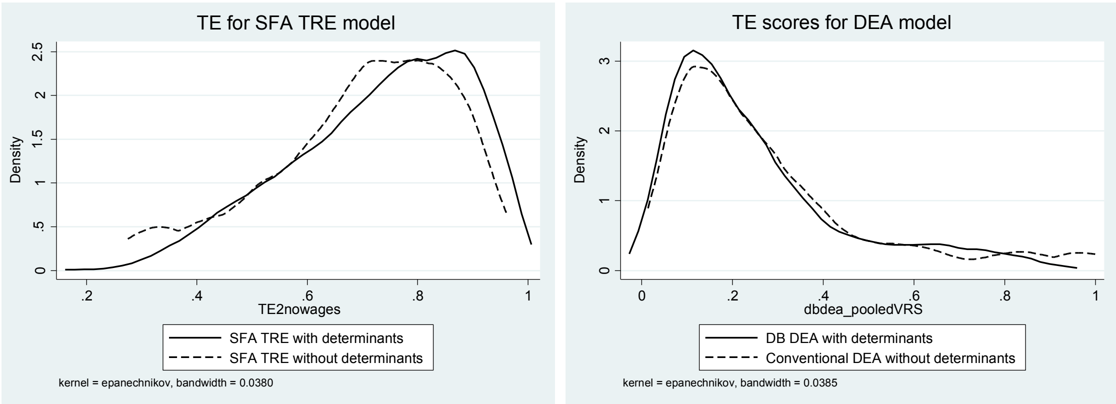


Table 1: Description of variables used

Variables	Description
Output	
Y_{it}	Total revenues of performing arts firm, adjusted for inflation using CPI index.
Inputs	
Capital (C_{it})	Total assets of the performing arts firm. Total assets include tangible and intangible assets. They are adjusted for inflation using CPI index.
Labour (L_{it})	The number of full-time and permanent employees of the performing arts firms.
Contextual variables	
Subsidies	The amount of public funds received by the firms.
Size	Size categories: Size_1 = 0 - 10 employees; Size_2 = 11 - 50 employees; Size_3 => 50 employees (dichotomized in the final analysis).
Age	The age of the firm in years.
Area	'North_West' = 1 and 0 otherwise, 'North_East' = 1 and 0 otherwise, 'Centre of Italy' (the reference category) = 1 and 0 otherwise (the reference category), 'South_East' = 1 and 0 otherwise.

Table 2. Summary statistics for output, inputs and efficiency determinants 2005-2014.

Variable and Description	All firms	Operas	PA companies	Theatres
Continuous variables - Mean (SD)				
Y (Output in thousand EUR)	1866	10,221	728	1259
	(5220)	(12,779)	(1408)	(1252)
Capital (Capital stock in thousand EUR)	9191	77,297	719	2047
	(28,879)	(51,359)	(1489)	(2024)
Labour (The number of employees)	63	404	16	39
	(148)	(269)	(12)	33
Subsidies (The log of subsidies in EUR)	12.08	16.27	11.14	12.80
	(1.87)	(0.94)	(1.05)	.64
Age (Age of the firm in years)	20.98	17.28	18.56	29.28
	(11.8)	(12.13)	(10.84)	10.42
Categorical variables - Count in %				
size_1[a] (micro firms: 0 - 9 employees)	19.50	n/a	27.21	6.97
size_2 (small firms: 10 - 49 employees)	64.86	5.19	70.46	76.16
size_3 (medium firms: 50 - 249 employees)	6.22	6.49	2.32	16.86
size_4 (large firms: ≥ 250 employees)	9.40	8.83	n/a	n/a
North_West (Dummy = 1 for North-west region)	24.61	29.87	20.04	34.88
North_East (Dummy = 1 for North-East region)	19.92	32.46	12.44	34.88
Centre[a] (Dummy = 1 for Central region)	30.56	3.89	33.33	19.18
South_Islands (Dummy = 1 for South Islands)	24.89	33.76	34.17	11.04
No. firms	146	12	105	29
No. observations	723	77	474	172

[a] denotes the reference category.

Table 3. SFA results for Italian PA firms over the period 2006-2014

	TRE Model			TREM Model		
Dependent variable: lnY_{it}	(1)	(2)	(3)	(4)	(5)	(6)
			Translog Production Function Coefficients			
lnCapital (β_1)	0.726***	0.726***	0.518***	0.724***	0.724***	0.728***
	(0.026)	(0.026)	(0.020)	(0.116)	(0.117)	(0.115)
lnLabour (β_2)	0.167***	0.165***	0.143***	0.160***	0.159***	0.159***
	(0.026)	(0.026)	(0.024)	(0.051)	(0.051)	(0.051)
0.5lnCapital^2 (β_{11})	0.053***	0.052***	-0.004	0.113***	0.113***	0.114***
	(0.013)	(0.013)	(0.012)	(0.040)	(0.041)	(0.040)
0.5lnLabour^2 (β_{22})	0.012	0.010	0.004	0.016	0.016	0.016
	(0.017)	(0.019)	(0.017)	(0.026)	(0.026)	(0.026)
lnCapital_lnLabour (β_{12})	0.041***	0.042***	0.038***	0.044**	0.043*	0.043**
	(0.012)	(0.012)	(0.012)	(0.022)	(0.022)	(0.022)
year_ 2007	-0.008	-0.009	-0.016	-0.008	-0.008	-0.011
	(0.090)	(0.089)	(0.091)	(0.095)	(0.095)	(0.095)
year _2008	0.012	0.011	0.009	0.020	0.019	0.017
	(0.057)	(0.057)	(0.058)	(0.059)	(0.059)	(0.059)
year _2009	-0.026	-0.026	-0.023	-0.018	-0.019	-0.021
	(0.062)	(0.062)	(0.061)	(0.066)	(0.066)	(0.065)
year _2010	-0.129**	-0.130**	-0.132**	-0.139**	-0.139**	-0.144**
	(0.064)	(0.065)	(0.064)	(0.065)	(0.065)	(0.065)
year _2011	-0.223***	-0.223***	-0.222***	-0.224***	-0.223***	-0.228***
	(0.051)	(0.051)	(0.052)	(0.052)	(0.052)	(0.052)
year _2012	-0.262***	-0.263***	-0.263***	-0.262***	-0.262***	-0.265***
	(0.048)	(0.048)	(0.048)	(0.049)	(0.049)	(0.049)
year _2013	-0.301***	-0.301***	-0.299***	-0.303***	-0.303***	-0.307***
	(0.053)	(0.053)	(0.053)	(0.055)	(0.055)	(0.055)
year _2014	-0.288	-0.289***	-0.289***	-0.292***	-0.291***	-0.297***
	(0.049)	(0.050)	(0.050)	(0.051)	(0.051)	(0.051)
			Firm type indicators			
Operas	-1.150***	-	-	-1.654***	-	-
	(0.103)			(0.105)		
PA companies	0.058*	1.201***	-	0.491***	2.165***	-
	(0.031)	(0.110)		(0.032)	(0.112)	
Theatres	-	1.143***	-	-	1.677***	-
		(0.103)			(0.105)	
Random parameter (w_i)	yes	yes	yes	yes	yes	yes
Within group means	no	no	no	yes	yes	yes
			(In)efficiency determinants			
δ_1 (subsidies)	-0.182***	-0.185***	-0.183***	0.098*	-0.095*	-0.093*
	(0.049)	(0.050)	(0.049)	(0.054)	(0.054)	(0.054)
δ_2 (size – small)	-0.559***	-0.566***	-0.567***	-0.613***	-0.609***	-0.617***
	(0.093)	(0.094)	(0.091)	(0.100)	(0.100)	(0.100)
δ_3 (size – medium)	-2.664	--9.585	-8.474	-8.335	-8.470	-8.650
	(2.544)	(2.6x10^3)	(8.3x10^2)	(6.4x10^2)	(7.4x10^2)	(8.8x10^2)
δ_4 (size – large)	0.515	0.523	0.545*	0.039	0.018	0.008
	(0.319)	(0.322)	(0.315)	(0.354)	(0.354)	(0.354)
δ_5 (age)	-0.014***	-0.014***	-0.015***	-0.018***	-0.018***	-0.019***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
δ_6 (north_west)	-2.664**	-2.693**	-2.618***	-2.004***	-1.881***	-1.800***
	(1.061)	(4.7x10^2)	(0.995)	(0.634)	(0.564)	(0.531)
δ_7 (north_east)	-0.662***	-0.664***	-0.662***	-0.539***	-0.533***	-0.503***
	(0.120)	(0.121)	(0.116)	(0.121)	(0.121)	(0.122)
δ_8 (south_islands)	0.021	-0.019	-0.028	-0.010	-0.002	0.007
	(0.097)	(0.097)	(0.096)	(0.103)	(0.103)	(0.103)

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Table 3. Continued

Dependent variable: $\ln Y_{it}$	TRE Model			TREM Model		
	(1)	(2)	(3)	(4)	(5)	(6)
			Technical Efficiency Scores (TE_{it})			
Mean	0.735	0.735	0.732	0.743	0.745	0.737
Standard Deviation	0.155	0.155	0.158	0.144	0.143	0.147
Minimum	0.199	0.199	0.199	0.236	0.236	0.234
Maximum	0.966	0.965	0.968	0.963	0.964	0.966
Returns to scale	0.893	0.891	0.661	0.884	0.883	0.887
No. Firms (observations)	146 (723)	146 (723)	146 (723)	146 (723)	146 (723)	146 (723)
λ – parameter	1.289	1.304	1.298	1.278	1.272	1.269
Log-Likelihood	-404.2	-404.2	-409.3	-380.3	-380.84	-388.2

Table 4. Double bootstrap DEA results for PA firms over the period 2006-2014.

Sample	**All PA firms**	LB	UB	**Operas**	LB	UB	**Companies**	LB	UB	**Theatres**	LB	UB
						(In)efficiency determinants						
log subsidies (δ_1)	-26.436***	-50.918	-12.456	2.968***	0.579	6.202	-49.93***	-77.204	-32.275	3.115*	0.575	5.880
small size (δ_2)	-31.755**	-64.869	-6.991	na	na	na	-44.91***	-98.336	-3.926	18.060***	4.481	36.023
medium size (δ_3)	-100.83***	-220.38	-25.381	-5.796*	-12.099	-1.276	-55.615*	-103.85	-4.349	20.140***	7.666	36.722
large size (δ_4)	106.88***	27.143	231.714	Base cat.	Base cat.	Base cat.	na	na	na	na	na	na
age (δ_5)	4.987***	2.681	9.371	1.268***	0.741	1.994	7.366***	4.803	12.064	0.607***	0.302	1.062
north_west (δ_6)	9.433	-57.42	67.961	-36.74***	-59.839	-19.238	-29.398	-118.15	31.574	4.096	-4.829	16.572
north_east (δ_7)	70.231***	17.769	156.99	-1.964	-9.622	8.450	134.54***	72.265	224.50	1.998	-8.760	14.247
south_islands (δ_8)	107.942***	52.892	217.41	6.142**	0.431	12.735	137.28***	86.622	223.59	10.936***	0.263	24.939
						VRS Technical Efficiency (TE_{it}) Scores						
Mean	0.251	0.276	0.234	0.316	0.277	0.370	0.254	0.235	0.279	0.304	0.274	0.350
Standard Deviation	0.196	0.221	0.180	0.282	0.250	0.329	0.193	0.176	0.217	0.204	0.179	0.243
Minimum	0.011	0.013	0.010	0.057	0.048	0.069	0.012	0.010	0.013	0.034	0.028	0.038
Maximum	0.921	1.023	0.884	0.906	0.843	1.017	0.927	0.881	0.998	0.852	0.787	0.989
						Scale Efficiency (SE_{it})						
Mean	0.852	0.819	0.819	0.997	0.964	1.043	0.951	0.937	0.975	0.949	0.939	0.975
Standard Deviation	0.304	0.288	0.288	0.141	0.138	0.172	0.150	0.147	0.161	0.146	0.152	0.161
No. firms	146			12			105			29		
No. observations	723			77			474			172		

* significant at 10%; ** significant at 5%; *** significant at 1%. A negative sign indicates a negative effect on ϕ and hence a positive effect on TE and vice versa.

Table 5. Summary statistics of TE scores.

Models/sample	All firms	Operas	Companies	Theatres
TRE	0.735 (0.155)	0.726 (0.139)	0.718 (0.165)	0.786 (0.121)
TREM	0.735 (0.155)	0.726 (0.139)	0.718 (0.165)	0.785 (0.121)
DB DEA	0.251 (0.196)	0.316 (0.282)	0.254 (0.193)	0.304 (0.204)

Mean values. Standard errors in parentheses.

Table 6. Spearman rank correlations between the TE scores for different models.

		SFA TE scores from Table 3					
		(1)	(2)	(3)	(4)	(5)	(6)
SFA TE scores from Table 3	(1)	1					
	(2)	0.908	1				
	(3)	1	0.908	1			
	(4)	0.917	0.999	0.918	1		
	(5)	0.987	0.890	0.987	0.902	1	
	(6)	0.907	0.962	0.907	0.961	0.913	1
DB DEA TE score for the pooled sample from Table 4	(7)	0.703	0.750	0.703	0.747	0.710	0.789