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Are public state libraries efficient? An empirical assessment using network Data Envelopment Analysis

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ABSTRACT

In Italy, public state libraries are multi-product organizations preserving ancient books of great historical relevance for future generations, and providing divisible services to the public. Hence, they may undertake different activities for conservation and use, which together constitute a network. This paper shows the importance of considering multi-process interactions in evaluating the overall performance of public state libraries and focuses on library operations and their sub-processes. It uses a network two-stage Data Envelopment Analysis (DEA) approach to examine the relationship between the libraries' basic inputs, intermediate outputs and final outputs. The main result is that Italian public state libraries generally perform better in the first stage of conservation, but score poorly in the second stage of use. Some policy advice to improve the decision-making process follow

1. Introduction

In Italy, there is a unique set of libraries – public state libraries – with the distinctive feature of having outstanding and rich historical collections. They perform an interesting nexus of conservation and use functions, providing divisible services to the public as well as preserving ancient books and other items of great historical relevance for future generations.

This paper aims at investigating the efficiency of these libraries using a network DEA efficiency approach based on the pioneer works of Färe and Grosskopf [1,2]. Specifically, we apply the centralized network DEA estimator proposed by Liang et al. [3] and refined by Kao and Hwang [4]. In the production structure we assume that, at stage one, libraries' managers combine resources (infrastructure, equipment, expenditure, personnel) to perform a set of internal operations necessary to generate 'intermediate outputs' aimed at preserving and/or improving the collections to be made available to users. At stage two, these 'intermediate outputs' are used as inputs for the delivery and consumption of public state libraries' 'final outputs'. Thus, in the first stage we assess the ability of the public state libraries to utilize the resources efficiently for the conservation of the historical collections while, in the second stage, we evaluate the ability to use collections for the provision of divisible services.

The present study adds to the previous empirical literature on the efficiency of cultural institutions in several ways. Firstly, the study represents, to the best of our knowledge, the first attempt to investigate the technical efficiency of cultural organizations, using the centralized network DEA estimator proposed by Liang et al. [3].[1]

Secondly, contrary to previous studies on cultural institutions, we assess the efficiency of public state libraries, using both the standard DEA estimator and the centralized network DEA estimator. Thus, we are able to better investigate the role of intermediate outputs for the performance, and to identify the specific sources of inefficiency embedded in the interactions between conservation and use activities.

Thirdly, since traditional DEA statistical estimators of the frontier are obtained from finite samples, the corresponding measures of efficiency are sensitive to the sampling variations of the frontier obtained [5]. Therefore, in this paper, we employ a consistent bootstrap estimation procedure [6] that enables us to assess the sensitivity to sampling variations and to provide a robustness check of our findings in baseline DEA estimator. Moreover, because the two-stage network DEA estimator is quite sensitive to scale assumption [7], the bootstrap procedure allows us to robustly test for returns to scale by using the algorithm proposed by Simar and Wilson [8].

Finally, to assess the role of historical collections for the efficiency of public state libraries we employ both the physical and monetary

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[1] As it is reported in the literature review section, there are some studies (e.g. Refs. [23,28] that propose a multi-stage approach. However, they apply the early approach introduced by Wang et al. [27] and Seiford and Zhu [26], which assesses the efficiency of the two stages separately without considering possible conflicts between the different stages.

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values of the assets managed by public state libraries. To the best of our knowledge, this is the first attempt to assess the performance of cultural institutions using both measures. The main result is that Italian public state libraries generally perform better in the first stage of conservation, but score poorly in the second stage of use.

The remainder of the paper is structured as follows. Section 2 provides a review of the previous literature. Section 3 analyses the main institutional and organizational features of Italian public state libraries. Section 4 describes our methodological framework, the data and the empirical strategy. Section 5 presents the empirical results. Finally, Section 6 provides some concluding remarks.

2. Setting the stage: a review of the previous literature

In this Section we provide a survey of the previous literature on the assessment of the efficiency of various types of cultural organizations (e.g. museums, libraries, theatres, heritage authorities) with different institutional goals and models of production, special attention is given to studies focusing on libraries. As we pointed out before, our analysis refers to a somewhat 'special' type of library that performs a nexus of conservation and use functions. The economic investigation of the efficiency and, more in general, of the performance of public cultural services is longstanding, though less widespread if compared with other sectors such as health or education [9]. From the perspective of performance assessment, there is a broad range of measures and methods [10]. Generally, the bulk of these measures and methods have focused on efficiency. There are, however, different notions of efficiency: technical efficiency, efficiency of scale, allocative efficiency or cost minimisation [9]. The last one is frequently used, but it is possible to question whether it provides a proper measure of the performance of cultural institutions.

Whatever approach is adopted; the underlying assumption is that it is possible to choose the optimal combination of inputs to obtain the desired outcome. However, such an assumption is rarely true for cultural institutions, especially for the public ones. In this case, cultural institutions operate under severe constraints even more so with the general reduction of public funds that has characterised most Western countries since 2008 [11]. Acknowledging this limit, several studies have concentrated on technical efficiency intended as the capacity 'to achieve an output using fewer resources or to produce the maximum output given a certain set of resources' ([9]: 473). To consider this, several studies (e.g. Refs. [12–19]) have used frontiers to measure the efficiency of cultural institutions.

Two main analytical approaches are available to estimate efficiency frontiers: parametric (Stochastic Frontier Analysis, SFA) and non-parametric (mainly Data Envelopment Analysis – DEA, and Free Disposal Hull – FDH). Although in principle, both parametric and non-parametric approaches are suitable to assess the performance of cultural institutions, a large number of empirical studies have used the latter. The reasons are probably connected to the flexibility of the non-parametric frontier approach that is a useful tool to assess the relative efficiency of cultural organizations.[2] Stroobants and Bouckaert [20] provide a survey of studies using nonparametric frontier methods for libraries.

Independently from the analytical approach used, studies trying to assess the efficiency of cultural organizations face the challenge of characterising the relationship between inputs and outputs. Sometimes the problem relates to the identification of the output(s) and, in some cases, the outcome(s) of cultural institutions. When focusing on the efficiency of libraries, Chen [21] considers five inputs (staff, collection, acquisition expenditure, library space, seating capacity) and six outputs (attendance, book circulation, reference transaction, reader satisfaction, service hours and inter-library loans). Vitaliano [22] and Hammond [23] use as outputs: the yearly number of items lent, the number of enquiries processed and the number of requests for specific items processed; the inputs are: opening hours; the collection of books and audio-visual material; the number of subscriptions and acquisitions.[3] Miidla and Kikas [24] consider four inputs – yearly acquisition expenditures, yearly salary expenditures, collection size and floor area, and two outputs – the number of readers and number of loans. De Carvalho et al. [25] use as inputs: number of employees, area and number of volumes, and they consider consultations, loans, enrollments and user traffic, as outputs.

Recent studies about libraries use multi-stage models and also take into account the potential outcome deriving from the consumption of library services. The early multi-stage studies [22,23], in contrast with single-stage DEA models [57], consider a possible internal structure of libraries production to evaluate their efficiency. In fact, in the presence of internal structures, single-stage DEA models are not sufficient; therefore, two-stage or network DEA models are needed. However, these studies use the most straightforward network two-stage structure, where all inputs are supplied to the first stage to produce intermediate outputs, that are used in the second stage to provide the final outputs [26,27]. Moreover, the authors assess the efficiency of the two stages separately, without considering possible conflicts between the different stages.

Similar to Hammond [23] with regard to the basic two-stage structure, Simon et al. [28] analyse the productivity growth of 34 Spanish university libraries using a Malmquist productivity index. The library production system is described as composed of three processes: internal production, service delivery, and impact of services on users. More specifically, Simon et al. [28] propose a model with three stages where, at stage one, library managers combine resources as personnel, expenditures, and equipment to generate intermediate outputs aimed at increasing the collection and improving the infrastructure. In the second stage, these intermediate outputs are used by personnel and users (*i.e.* final outputs). In the final stage, the short and medium-term impact of services on users and institutions is considered as the outcome. Similar to Seiford and Zhu [26], the authors apply a generalization of the basic two-stage structure, which allows both stages to consume exogenous inputs supplied from outside, and to produce final outputs in each stage without considering possible conflicts between the different stages.[4]

Looking at the outcomes of libraries, De Witte and Geys [29] employ a conditional robust FDH estimator and characterize the library production process as a two-stage setting. More specifically, for the first stage they use the robust FDH estimator, proposed by Cazals et al. [30], to translate basic inputs (personnel, operating expenditure, infrastructure) into service potential (available books and media, opening hours). In the second-stage they employ the conditional FDH estimator, proposed by Daraio and Simar [31,32][5], to assess how these outputs are transformed into observed outcomes. However, De Witte and Geys [29] find that the final outcome depends on the characteristics of demand, which is usually beyond the control of the library. Hence they argue that for a fair assessment of efficiency one should concentrate mainly on the first stage. De Witte and Geys [33] follow the same line of reasoning when evaluating the role of citizens as co-producers of the services provided by local public libraries in Flanders. They show that the use of

[2] Pignataro [45] and Fernández-Blanco et al. [9] provide surveys about the use of these techniques in the cultural sector while a limited number of studies use SFA to assess library performance [46].

[3] From a different perspective Reichmann and Sommersguter-Reichmann [47]; using a sample of 118 university libraries from Australia, Austria, Canada, Germany, Switzerland and the United States, address the problems of differing environments and their effects on library performance.

[4] Such conflicts may arise because intermediate outputs are not treated simultaneously [48,49].

[5] For a recent application of the estimator [31,32] in the cultural sector see Guccio et al., [58].

final outcomes, as an output variable in efficiency studies, leads to biased inferences when evaluating the pure productive efficiency of public service provision. These last results are relevant for our analysis since there is often a trade-off between the different objectives of cultural organizations (e.g. use *vs*. conservation), which makes it difficult to identify the outputs and outcomes affecting the result of the analysis of efficiency.

3. Italian public state libraries: activities and organization

In Italy, there are 46 public state libraries, which are managed by the Ministry for Heritage, Cultural Activities and Tourism (*Ministero dei Beni e delle Attività Culturali e del Turismo* MIBACT),[6] through the *Libraries and Cultural Institute General Directorate (DGBIC)*.[7] They have wide and rich historical collections, consisting of almost 40 million items, including manuscripts, printed volumes, *incunabula,*[8] *cinquecentine,*[9] maps, music scores and drawings.[10] The public state libraries' mission is wide: they conserve and enhance their historical collections, collect and conserve Italian and international publications related to their collections, and provide services to the public offering information on their collections and allowing the circulation of books and other documents. Fig. 1 shows Italian public state libraries' geographical location at provincial level and Table 1 lists them.

Public state libraries are part of the national network of Italian libraries: the National Library System (SBN).[11] However, because of their 'core' function, i.e. conserving historical collections, Italian public state libraries exhibit distinctive features, which also make them different from the libraries usually investigated in the literature. These libraries represent a rather heterogeneous set resulting from a complex stratification with three historical cores:[12] ecclesiastic ones, libraries dating back from the Renaissance to Post-Unitarian time, and Pre-Unitarian University libraries. It is worth noting that the university libraries included in the sample are different from 'common' university libraries. In fact the former are owned and managed by the MIBACT, while the latter are managed by universities, and provide services for research and education.[13]

Two public state libraries (in Rome and Florence) are labelled 'national' and have the right of legal deposit, i.e. the legal requirement that publishers have to deposit a copy of everything published in Italy in these libraries.[14] Moreover, unlike other peripheral MIBACT institutions, such as historical archives, national libraries are not necessarily located in provincial capital towns. On the contrary, they are in cities of different size, even in very small ones, and their geographical distribution is also quite uneven across Regions. Notwithstanding this heterogeneity, mainly relying on historical reasons, these institutions share the 'core' function, i.e. the conservation of historical collections, which is the priority for all of them and, therefore, strongly affects their behaviour in a common direction.

Within the national statistic programme, MIBACT carries out a yearly investigation on public state libraries, collecting data on their inputs and outputs. Using these data, a recent study of the Italian Ministry of Economy and Finance – State General Accounting Department (*Ragioneria Generale dello Stato* – [34] provides a clear picture of the varied dimensions of public state libraries with respect to the size of collections, the number of users, the personnel size. The study also offers some partial indicators of productivity, which show a high variability across libraries.

It is also worth noting that the Italian Ministry of Economy and Finance – State General Accounting Department [35] officially provides a financial measure of the monetary value of the collections of state public libraries, as components of the State patrimony. Hence, to assess the role of historical collections for the efficiency of public state libraries we are able to employ both the physical and monetary values of the assets managed by public state libraries.

4. Methods, data and empirical strategy

4.1. Methodology

The literature mentioned in the previous Section has adopted different multi-stage models (e.g. Refs. [23,28]), with the application of standard DEA methodology in each stage, without considering possible conflicts between the different stages [36]. In this paper, we assess the efficiency of Italian public state libraries, under different assumptions on the role of conservation of historical collections, and using a different empirical strategy. More specifically, we use the centralized network DEA model proposed by Liang et al. [3] that permits the examination of a sequence of production technologies: in a first stage, inputs produce intermediate outputs that become inputs in the second stage, where the final outputs are produced.[15] Following Zhu [37], first we apply the standard DEA estimator to Italian public state libraries (our Decision Making Units DMUs) with reference to the year 2011. Then, the centralized network DEA estimator is employed.

To describe the centralized network DEA estimator,[16] it is assumed that *n* DMU_j $(j = 1, 2, \ldots, n)$ have to be evaluated. Under the centralized network DEA model the inputs and outputs of *j-th* DMUs can be grouped into a two-stage process, intermediate outputs needs to be included. Namely, the DMU_j has *m* inputs x_{ij} $(i = 1, 2, \ldots, m)$ to the first stage, and *D* outputs z_{jd} $(d = 1,2, \ldots., D)$ from that same stage. These *D* outputs then become the inputs to the second stage whereas y_{rj}, $(r = 1, 2, \ldots, s)$ are the *r* outputs of that stage. Thus, in general two-stage processes, it is assumed that for DMU_j we might define the following efficiency measure of each stage:

$$\theta_j^1 = \frac{\sum_{d=1}^{D} w_d z_{dj}}{\sum_{i=1}^{m} v_i x_{ij}} \text{ and } \theta_j^2 = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{d=1}^{D} \widetilde{w}_d z_{dj}} \tag{1}$$

where θ_j^1 and θ_j^2 denote respectively the efficiency in the first and in the second stage and v_i, w_d, $\widetilde{w}_d$ are unknown non-negative weights. Note that in (1) w_d can be equal to $\widetilde{w}_d$. The centralized model assumes that the relationship between overall efficiency and individual stage efficiencies is multiplicative. Then we might assume that the global efficiency measure θ_j^G is the product of the efficiency measure in each stage:

$$\theta_j^G = \theta_j^1 \theta_j^2 \tag{2}$$

Therefore, assuming that $w_d = \widetilde{w}_d$, the model (2) becomes $\sum_{r=1}^{s} u_r y_{r0} / \sum_{i=1}^{m} v_i x_{i0}$ and we have the following fractional program:

[6] Public state libraries have been recognized and organized in 1995. Originally, they were 47; however, since 2006 the University Library of Bologna is supervised by the Ministry of Education, University and Research.

[7] The organization of the MIBACT has been reformed in 2014; detailed information on the organization of the DGBIC can be found at http://www.librari.beniculturali.it.

[8] A pamphlet that was printed – not handwritten – before 1501.

[9] They are 16th century books.

[10] As for November 2016, see http://www.librari.beniculturali.it/opencms/opencms/it/biblpubbliche/.

[11] More than 4.000 public and private libraries join the system, which is coordinated at the central level, with an online catalogue referring to a multimedia database of almost 10 million records.

[12] For a detailed description of the different types of Italian public state libraries see, http://www.librari.beniculturali.it/opencms/opencms/it/biblpubbliche/biblioteche.

[13] In fact, as mentioned, the University Library of Bologna, in 2006 passed under the supervision of the Ministry of Education, University and Research.

[14] These institutions are granted special autonomy.

[15] For a thorough discussion of different network DEA models, see Ref. [48] and Kao [49].

[16] For further details, see Ref. [7].

Fig. 1. Geographical distribution of Italian public state libraries. *Source:* MiBACT: http://www.librari.beniculturali.it.

$$\theta_j^G = Max\theta_j^1\theta_j^2 = Max\sum_{r=1}^{s} u_r y_{r0} / \sum_{i=1}^{m} v_i x_{i0}$$
s.t.
$$\theta_j^1 \le 1,$$
$$\theta_j^2 \le 1,$$
$$w_d = \widetilde{w}_d. \tag{3}$$

Model (3) can be converted into the following linear program that represents the two-stage centralized DEA model:

$$\theta_j^G = Max\sum_{r=1}^{s} u_r y_{r0}$$
s. t.
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} w_d z_{dj} \le 0,\ j = 1,2,\ \ldots..,\ n,$$
$$\sum_{d=1}^{D} w_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \le 0,\ j = 1,2,\ \ldots..,\ n,$$
$$\sum_{i=1}^{m} v_i x_{i0} = 1,$$
$$w_d \ge 0,\ d = 1,2,\ \ldots.,D;\ v_i\ \ge 0,\ i = 1,2,\ldots,m;\ u_r \ge 0,\ r = 1,2,\ \ldots.,s. \tag{4}$$

Assuming that model (4) generates a unique solution, the efficiencies for both stages are presented as follows:

$$\theta_j^{1,G} = \frac{\sum_{d=1}^{D} w_d^* z_{dj}}{\sum_{i=1}^{m} v_i x_{ij}} = \sum_{d=1}^{D} w_d^* z_{dj},\ \text{and}\ \theta_j^{2,G} = \frac{\sum_{r=1}^{s} u_r^* y_{rj}}{\sum_{d=1}^{D} \widetilde{w}_d z_{dj}} \tag{5}$$

where $\theta_j^{1,G}$ and $\theta_j^{2,G}$ are, respectively the efficiency for the first and the second stage.

Fig. 2 depicts our centralized network DEA model for Italian public state libraries. The model comprises two stages. Given j libraries, in the first stage i inputs x_{ij} produce intermediate D outputs z_{dj} of conservation (i.e. conserving and/or improving the historical collections to be made available to users). In the second stage, z_{dj} become intermediate D inputs in the process of use of y_{rj} that produce r final outputs. Fig. 2 also represents the traditional DEA one-stage model in which inputs and intermediate outputs (pooled together) are employed to produce the final outputs.[17]

4.2. Data

Our sample consists of 44 Italian public state libraries for the year 2011.[18] Data are obtained from two sources: MIBACT and RGS. Summary statistics for all the variables are reported in Table 2.

[17] We employed personnel only in the first stage because the centralized network model proposed by Kao and Hwang [4] does not allow to use exogenous inputs in the second stage. In fact, for such class of two-stage network models, all inputs from outside are supplied in the first stage, to produce intermediate outputs for the second stage that produce the final outputs [49]. Our choice to use personnel only in the first stage is also due to comparisons with standard DEA model applications [37].

[18] We exclude the libraries *Girolamini* in Naples and *Abbazia di Farfa* near Rome because some data are not available for the year 2011.

Table 1
Italian public state libraries.
Source: our elaboration on data provided by MiBACT website http://www.librari.beniculturali.it.

Province	Library	Foundation
Turin	Biblioteca Nazionale Universitaria	1723
Turin	Biblioteca Reale	1831
Cremona	Biblioteca Statale	XVII Century
Milan	Biblioteca Nazionale Braidense	XVIII Century
Pavia	Biblioteca Universitaria	1754
Padua	Biblioteca Statale del Monumento Nazionale dell'Abbazia Benedettina di S. Giustina	X Century
Padua	Biblioteca Universitaria	1629
Padua	Biblioteca Statale del Monumento Nazionale di Praglia	XII Century
Venice	Biblioteca Nazionale Marciana	1537
Gorizia	Biblioteca Statale Isontina	1621
Trieste	Biblioteca Statale "Stelio Crise"	1956
Genova	Biblioteca Universitaria	1604
Modena	Biblioteca Estense Universitaria	1598
Parma	Biblioteca Palatina	XVIII century
Florence	Biblioteca Marucelliana	1752
Florence	Biblioteca Medicea Laurenziana	1571
Florence	Biblioteca Nazionale Centrale	1714
Florence	Biblioteca Riccardiana	XVI Century
Lucca	Biblioteca Statale	XVII Century
Pisa	Biblioteca Universitaria	1742
Macerata	Biblioteca Nazionale	1990
Frosinone	Biblioteca Statale del Monumento Nazionale di Trisulti	XI Century
Frosinone	Biblioteca Statale del Monumento Nazionale di Casamari	XII Century
Frosinone	Biblioteca Statale del Monumento Nazionale di Montecassino	VI Century
Rome	Biblioteca Angelica	1604
Rome	Biblioteca Casanatense	1701
Rome	Biblioteca del Monumento Nazionale dell'Abbazia di Farfa	V-VI Century
Rome	Biblioteca di Storia Moderna e Contemporanea	1880
Rome	Biblioteca Medica Statale	1925
Rome	Biblioteca Statale "Antonio Baldini"	1962
Rome	Biblioteca Nazionale Centrale "Vittorio Emanuele II"	1876
Rome	Biblioteca Universitaria Alessandrina	1667
Rome	Biblioteca Vallicelliana	1565
Rome	Biblioteca Statale del Monumento Nazionale di Grottaferrata	XI Century
Rome	Biblioteca Statale del Monumento Nazionale di S. Scolastica	IX Century
Rome	Biblioteca di Archeologia e Storia dell'Arte	1922
Avellino	Biblioteca statale del monumento nazionale di Montevergine	XII Century
Naples	Biblioteca Statale Oratoriana dei Girolamini	1586
Naples	Biblioteca Nazionale "Vittorio Emanuele III"	XVIII Century
Naples	Biblioteca Universitaria	1615
Salerno	Biblioteca Statale del Monumento Nazionale di Badia di Cava	XI Century
Bari	Biblioteca Nazionale "Sagarriga Visconti Volpi"	1865
Potenza	Biblioteca Nazionale	1985
Cosenza	Biblioteca Nazionale	1882
Cagliari	Biblioteca Universitaria	1764
Sassari	Biblioteca Universitaria	1765

As De Witte and Geys [29] notice, the choice of the variables used in the analysis is fundamental to avoid biased results. In our case, libraries perform two main activities: conservation of cultural heritage and provision of divisible services to users. Hence, focusing only on variables related to the latter, libraries might appear inefficient, whereas they might be very efficient as for the conservation function. On the input side, we distinguish between current and capital inputs. In the related literature previously reported, current inputs are generally personnel and expenditures, as well as libraries collections of books, manuscripts, periodicals and other collections. In our sample, the following inputs are available: number of personnel (PERS)[19]; current library expenditure (EXP), excluding current labour costs[20]; capital resources are measured using two variables: the total shelves' dimension in linear meters (SHELF), and the number of seats available for reading and consultations (SEAT).

Because of our approach we treat libraries collections of books (BOOKS)[21]; manuscripts (MANUSCRIPT); periodicals (PERIODICAL); and other collections (OTHER_COLLECTIONS)[22] as intermediate outputs. In addition, to assess the role of historical collections' value, we use as a proxy the financial value of the assets (ASSET) managed by public state libraries. This indicator can be considered a sound measure of value since it is officially used to evaluate State assets by RGS, *i.e.* the institution responsible for the consistency and reliability of national accounts. The evaluation criteria are established by the Government and are quite detailed.[23] We believe that using both physical and monetary measures provides a good proxy for the overall significance of collections. However, to better disentangle the marginal effects of the two measures, in what follows we also employ a model that use only the physical measure. In our two-stage model, both current and capital inputs are used to fulfil the two main activities of public state libraries: conservation (i.e. preserving and/or improving the historical collections to be made available to users) and use (i.e. readers visits, circulation of various types of material, interlibrary loan activity, etc.). On the contrary, in the traditional one-stage approach these resources are pooled to realise the use function.

With reference to the final outputs, annual data for Italian public state libraries include: readers' visits and attendance (READERS); consultation of different types of items (CONSULTED_ITEMS); number of users' requests and enquiries processed (LOAN); inter-library loan activity (INTER_LOAN). Because of data (un)availability, we are not able to catch all the aspects of the use function. As a matter of fact, we do not have data about other possible outputs, such as exhibitions that libraries might organise to boost users' numbers, nor do we consider the online and digital use of libraries. As evident from Simon et al. [28]; this certainly corresponds to an underestimation of the productivity, hence of the efficiency, of these institutions. However, neglecting online and digital uses does not undermine the comparability of results. In fact, as mentioned, our sample consists of libraries having conservation as the 'core' common function, whatever their institutional and historical features. Therefore, the lack/presence of digital use affects their use in a similar way.

4.3. *Empirical strategy*

4.3.1. *Public state libraries' production models and sensitivity analysis*

In Table 3 we report the proposed models for assessing the efficiency of our sample of Public State Libraries described in the previous section.

As for the models proposed, our relatively small sample might be a limitation in our empirical assessment. In fact, the relatively small number, n, of DMUs with respect to the dimensionality space (i.e., the number of input and output variables in the efficiency analysis) causes a severe problem for DEA estimations. However, it must be noted that,

[19] Unfortunately, data on labour cost are not available.

[20] EXP includes operation and maintenance, purchase and conservation of bibliographic material, and various minor expenditures (telephone, mail, travels, etc.).

[21] Including the number of *incunabula* and *cinquecentine* owned by each library.

[22] In this category graphics, microfilms, and multimedia items are included.

[23] Firstly, it recognizes that the value of movable historical collections increases over time. The value is calculated through an algorithm including several inputs. More precisely, the value of each item is assessed taking into account: i) an identification coefficient based on its characteristics and on its initial value when first included in the inventory; ii) the monetary appreciation rate provided by the National Institute of Statistics; iii) the scientific appreciation coefficient based, among other things, on the degree of conservation and on the quality; iv) the market value derived from the prices of the most important auction houses.

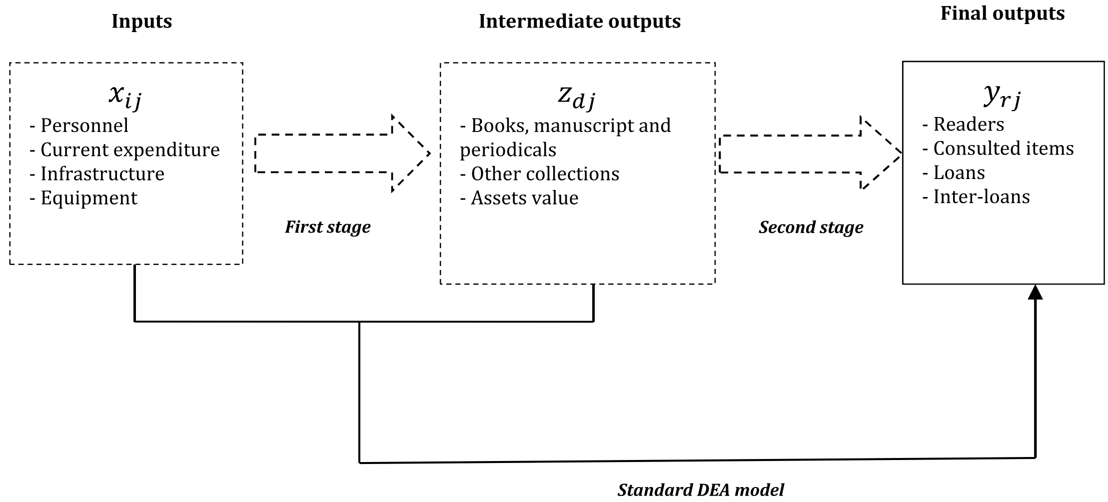

Fig. 2. Library's production models. *Source*: our elaboration.

Table 2
Descriptive statistics of employed variables.
Source: our elaboration on data provided by MiBACT Statistical office and RGS

Variables	Obs.	Mean	St. Dev.
Inputs			
PERS	44	39.31	47.35
EXP x 1000	44	502.67	651.17
SHELF	44	19,603.08	28,837.51
SEAT	44	136.47	167.35
Intermediate outputs			
ASSET x 1000	44	425,594.66	783,778.15
BOOKS	44	572,632.97	1,161,259.25
MANUSCRIPT	44	4,889.86	9,528.61
PERIODICAL	44	1,675.26	3,888.47
OTHER_COLLECTIONS	44	235,756.25	555,627.76
Final outputs			
READERS	44	35,981.50	47,786.96
CONSULTED_ITEMS	44	48,073.19	94,916.09
LOAN	44	4,802.19	6,586.43
INTER_LOAN	44	540.92	601.40

Note: monetary value in thousand euro at current price.

Table 3
The estimated models.
Source: our elaboration

Variable	MOD_1	MOD_2	MOD_3	MOD_4
Inputs				
PERS	◆	◆	◆	◆
EXP x 1000	◆	◆		
SHELF	◆			
SEAT	◆	◆	◆	◆
Intermediate outputs				
ASSET x 1000	◆	◆	◆	
BOOKS	◆	◆	◆	◆
MANUSCRIPT	◆	◆	◆	◆
PERIODICAL	◆	◆		
OTHER_COLLECTIONS	◆			
Final outputs				
READERS	◆	◆	◆	◆
CONSULTED_ITEMS	◆	◆	◆	◆
LOAN	◆	◆		
INTER_LOAN	◆	◆	◆	◆

for a given number of DMUs, the consistency of DEA estimates also depends on the number of inputs and outputs in the analysis. Kneip et al. [38] refer to this problem in non-parametric estimators as the "curse of dimensionality". It implies that small dimensionality spaces tend to produce better estimates for the efficient frontier than large dimensionality space.[24]

Our baseline model (MOD_1) largely overcomes the DEA convention that the minimum number of observations should be at least three times larger than the sum of the number of outputs and inputs [39]. Still, to control for the consistency of our estimates, we consider two other different models (MOD_2 and MOD_3) that employ progressively a smaller dimension in the input-output space. Namely, we first exclude variables based on correlation levels, because highly correlated variables are generally redundant and should not be included in the analysis [40].[25] In Table 4, we report the pairwise correlation matrix of our input-output variables. In MOD_2, we exclude the variables that for each group show a correlation higher than 90% (namely SHELF and OTHER_COLLECTIONS), whereas in MOD_3 we exclude the variables that for each group show a correlation higher that 80% (namely EXP x 1,000, PERIODICAL and LOAN). Furthermore, to better disentangle the role of monetary and physical value of the collections in the assessment of efficiency, we employ a model that uses only the physical value (MOD_4).

4.3.2. *Assessing for sampling variation and scale assumption*

In our efficiency assessment, we apply an output-oriented version of the model of Liang et al. [3] that, as mentioned, enables us to assess the overall efficiency as well as the efficiency of each stage. This choice follows most of the literature reviewed in Section 2, which assumes an output orientation. Moreover, data on libraries' collections for years other than 2011 show that they have increased over time.[26] Finally, it is reasonable to assume that in the short run both basic inputs and intermediate outputs are not likely to decrease, especially in public entities.

As stated in the previous Section, several studies have measured the efficiency of libraries applying non-parametric statistical techniques as DEA.[27] However, DEA estimators have also received some criticisms because they rely on extreme points and may be very sensitive to data selection, aggregation, model specification, and data errors. Nowadays,

[24] For a numerical example of the trade-off between sample size *n* and the number of inputs and outputs used for the consistency of efficiency estimate, see Simar and Wilson [42], p. 439.

[25] We are aware of the potential risks of distortion connected to the use of this rule [50]. However, it has to be noted that we report the estimates for all the models and use the rule proposed by Jenkins and Anderson [40] simply to check for the consistency of our estimates.

[26] See par. 4.2.

[27] For an introduction of the economic interpretation of DEA methods see Førsund [51], whereas, for a thorough survey of DEA applications see, among the others, [52].

Table 4
Pairwise correlation matrix between variables.
Source: our elaboration on data provided by MiBACT Statistical office and RGS

Variables		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	PERS	1.000												
(2)	EXP x 1000	0.803	1.000											
(3)	SHELF	0.787	0.918	1.000										
(4)	SEAT	0.763	0.770	0.751	1.000									
(5)	ASSET x 1000000	0.193	0.196	0.298	−0.023	1.000								
(6)	BOOKS	0.789	0.937	0.962	0.710	0.211	1.000							
(7)	MANUSCRIPT	0.371	0.337	0.406	0.189	0.363	0.413	1.000						
(8)	PERIODICAL	0.636	0.814	0.824	0.823	0.016	0.813	0.159	1.000					
(9)	OTHER_COLLECTIONS	0.724	0.925	0.948	0.660	0.243	0.987	0.395	0.819	1.000				
(10)	READERS	0.675	0.829	0.788	0.827	0.137	0.769	0.224	0.731	0.741	1.000			
(11)	CONSULTED_ITEMS	0.809	0.527	0.539	0.451	0.166	0.578	0.363	0.305	0.506	0.463	1.000		
(12)	LOAN	0.641	0.655	0.637	0.790	0.012	0.623	0.116	0.670	0.565	0.826	0.406	1.000	
(13)	INTER_LOAN	0.486	0.479	0.470	0.549	0.050	0.422	0.106	0.412	0.380	0.638	0.270	0.687	1.000

statistical inference in non-parametric frontier approaches is available mainly by using asymptotic sampling distributions or by using bootstrap [5].[28] Hence, to assess the sensitivity of the measured efficiency scores to sampling variations and to provide a robustness check of the findings in our baseline DEA model, we employ a consistent bootstrap estimation procedure [6]. Such a procedure allows us to approximate the sampling distribution of the estimator, to correct the bias and to construct confidence intervals of the efficiency estimates.[29] Furthermore, two-stage network DEA models are quite sensitive to scale assumption [7]. Thus, a test is needed to determine which scale characteristic is appropriate. Simar and Wilson [8] develop a test based on bootstrapping that examines the scale characteristic of the frontier. Within it, efficiency scores are estimated under all scale assumptions and in two steps it is tested whether there are significant differences between the efficiency scores under constant return to scale (CRS) and variable return to scale (VRS). In what follows we employ the bootstrap procedure proposed by Simar and Wilson [8] that allows us to robustly test for returns to scale in the baseline DEA model.

4.3.3. Outlier detection

Finally, we check for potential outliers in our sample. In non-parametric frontier several methods for outliers' detection have been proposed, but none of them can be considered as being able to detect all outliers under all circumstances. In fact, atypical observations can show the best or worse practices requiring different detection methods and bearing different consequences as only the super-efficient affect the best practice frontier. Furthermore, since our sample comprises, essentially, peripheral bodies under the same central institution, excluding some observations can bias the overall picture of libraries' efficiency assessment. Nonetheless, we perform some checks for outliers' detention using the inspection methods proposed by Wilson [41].[30] Using for detection the standard DEA estimator, we do not find a single or a small group of DMUs that systematically shows a super-efficiency coefficient (indicating potentially influential units in the sample that affect the best practice frontier) in all models (MOD_1, MOD_2, MOD_3 and MOD_4). Thus, prudentially, we give them the benefit of the doubt of not being an outlier.[31]

5. Results and discussion

In this Section we report the technical efficiency scores achieved by the different production function specifications shown in Table 2 and for the different approaches illustrated in Section 4. More specifically, assuming MOD_1 as a baseline, we first estimate libraries' efficiency using the standard DEA technique. Furthermore, we apply bootstrap techniques to assess the sensitivity of the measured efficiency scores to the sampling variations [6], and to provide a robustness check of scale assumption [8]. In Section 5.2 we will introduce the model of Liang et al. [3] that enables us to assess the overall efficiency as well as the efficiency of each stage. Finally, in Section 5.3 we report some robustness checks for potential outliers in our sample.

5.1. Baseline efficiency estimates

5.1.1. Standard DEA model

Table 5 shows the descriptive statistics for the technical efficiency estimates of our baseline model and, for convenience, also the estimates of models MOD_2, MOD_3 and MOD_4. The results reported in Table 5 show, in model (MOD_1) with constant returns to scale (CRS), an average technical efficiency score of 0.761. This indicates that the DMUs in our sample are, on average, relatively technically inefficient in the provision of services to users.[32] The large standard deviation, as well as the large difference between the minimum and maximum efficiency scores, indicates that there are considerable differences in the aggregate technical efficiency of the DMUs in our sample.

5.1.2. Assessing sample variation using bootstrap techniques

Table 5 also shows the efficiency scores of the other models (MOD_2, MOD_3 and MOD_4). Although, as expected, the average levels of efficiency decrease, the new efficiency estimates substantially confirm those in MOD_1. In fact, also in these models the estimates in Table 5 reveal that a large number of the DMUs in our sample works at an efficiency level far below one (the means are roughly around 0.70 in all cases). Furthermore, we find only slight differences between the estimates in MOD_3 and MOD_4 indicating that our efficiency

[28] To account for DEA traditional limitations, which do not allow for any statistical inference and measurement error, Simar and Wilson [6,53] introduced a bootstrapping methodology to determine the statistical properties of DEA estimators. The idea underlying the bootstrap procedure is to approximate the sampling distributions of efficiency scores by simulating their Data Generating Process - DGP [42]. However, some major issues remain regarding the use of asymptotic results and bootstrap: first, the high sensitivity of non-parametric approaches to extreme values and outliers and, second, the way to allow stochastic noises in a non-parametric frontier. Alternative approaches provide robust measures of efficiency at extreme data points based on partial frontiers and the resulting partial efficiency scores. A detailed survey of these approaches can be found in Simar and Wilson [5].

[29] For a detailed description see Simar and Wilson [5,42].

[30] This approach presents computational problems when the number of observations increase, thus Wilson [54] proposed a simpler screening methodology that, as the author explains, '(…) is less computationally intensive, and thus may be applied in much larger samples that the statistic proposed by Wilson [41]". However, as observed in Wilson [55] "with advances in computer technology, the outlier detection method described by Wilson [41] has become increasingly practical in terms of computational requirements". Accordingly, we use the software package FEAR 1.15 [56].

[31] All the estimates are available from the authors upon request.

[32] Table A.1 in Appendix A reports the efficiency estimates for each library in the sample.

Table 5
Statistics of the standard DEA efficiency estimates.
Source: our elaboration on data provided by MiBACT Statistical office and RGS

Models and estimators		Mean	St. Dev.	Min	Max
MOD_1	DEA (CRS)	0.7609	0.3064	0.1065	1.0000
	Bias corrected DEA (CRS) estimate	*0.7422*	*0.2992*	*0.1046*	*0.9862*
MOD_2	DEA (CRS)	0.7250	0.3262	0.0788	1.0000
	Bias corrected DEA (CRS) estimate	*0.7040*	*0.3166*	*0.0771*	*0.9857*
MOD_3	DEA (CRS)	0.6731	0.3358	0.0736	1.0000
	Bias corrected DEA (CRS) estimate	*0.6530*	*0.3259*	*0.0720*	*0.9766*
MOD_4	DEA (CRS)	0.6598	0.3408	0.0737	1.0000
	Bias corrected DEA (CRS) estimate	*0.6346*	*0.3217*	*0.0724*	*0.9817*

assessment is quite robust to different measures of historical collections.[33]

In order to test the sensitivity of the efficiency estimates to the variables used, we employ the bias-corrected efficiency scores.[34] In fact, the DEA efficiency estimate measures the performance relative to an estimation of the true and unobservable production frontiers and, thus, provides point estimates of performance. Since estimates on the frontier are based on finite samples, DEA measures based on these estimates are subject to sampling variation on the frontier. To address this problem, we implement a bootstrap procedure, with 2000 bootstrap draws as described by Simar and Wilson [6], to correct the bias in DEA estimates and obtain their confidence intervals. The results, reported for convenience also in Table 5, show that, from the perspective of sensitivity analysis, the efficiency estimate under a CRS assumption is robust with respect to sampling variation since there are only slight differences due to bootstrapping in the efficiency estimates in all models. Furthermore, to test more thoroughly the efficiency scores before and after the bias correction between the models, we use kernel density estimates of the efficiency scores that rely on the reflection method [42]. In this way, we are able to avoid the problems of bias and inconsistency at the boundary support.

In Fig. 3, we report the univariate kernel smoothing distribution [43] and the reflection method used to determine the densities of the performance estimates, respectively in MOD_1, MOD_2, MOD_3, and MOD_4.[35] The kernel density functions, reported in Fig. 3, allow us to confirm the above-mentioned results on the robustness of our efficiency estimates with respect to sampling variation and variables selection. In fact, only slightly differences in kernel density estimates are reported from MOD_4.[36]

Finally, as for the returns to scale assumption, the application of the test proposed by Simar and Wilson [8] shows that we cannot reject the null hypothesis of CRS at any conventional level of significance after conducting 2000 bootstrap replications.[37] Therefore, CRS should be considered as the underlying technology of the libraries under evaluation.[38]

5.2. Disentangling technical efficiency

The previous results show a large variation in the efficiency levels of the DMUs in our sample. However, they provide little insight into the sources of inefficiency, and the operational stages where inefficiency may arise. As mentioned, this happens because the standard DEA model treats efficiency evaluation as a 'black box', and fails to identify inefficiencies within the internal processes. Thus, in this Section we introduce the model of Liang et al. [3] that, instead, enables us to assess the overall efficiency as well as the efficiency of each stage.

Table 6 presents the results of the efficiency levels derived from the use of the two-stage network DEA model in the analysis of Italian public state libraries. We begin our discussion on network DEA two-stage in MOD_1, assumed as a baseline estimate. It is noteworthy that the median values for conservation efficiency (*stage 1*) are substantially higher than those for use efficiency (*stage 2*) – 0.6825 versus 0.3510, respectively. This indicates that Italian public state libraries tend to be more efficient, in comparative terms, in transforming physical and economic resources into the conservation and/or improvement of historical collections rather than in managing collections to make them available to users. These results are also found in MOD_2–0.5525 versus 0.3370, respectively – and, although smaller (0.3675 versus 0.3430), in MOD_3 confirming the consistency of our efficiency estimates. As we observed in standard DEA estimates, using only physical measures of collections (i.e. MANUSCRIPT and BOOKS) as in MOD_4 we found results (median value of 0.3658 in *stage 1* and 0.3422 in *stage 2*) that largely overlap with those obtained in MOD_3, further supporting the idea that the libraries in our sample seem to perform better in conservation activities, independently from the (financial/physical) measure of the collections used.

However, a caveat applies: the only data we have to describe and estimate conservation are those measuring the number and value of items. Hence, we are not evaluating the conservation function as such, e.g. restoration activities carried on by specialised staff. We consider that the number and value of items are good proxies for conservation activities, because these activities are closely related to the size and significance of collections. For the use function, we do not consider 'virtual' use of libraries because of the lack of data and, therefore, we only take into account 'physical' measures of such a function. We are aware that this might be a limitation of our analysis when comparing the efficiency of these libraries as for their use function.

Comparing the results in Table 6 with those obtained with DEA standard models (Table 5), not surprisingly the standard DEA model overstates the performance of Italian public state libraries. We expect this is because each standard DEA model proposed in Table 3, employs a larger set of input-output variables, compared to the corresponding single stage in the two-stage DEA model, and this results in higher efficiency.[39]

Furthermore, standard DEA fails to identify inefficiencies within the internal processes. Thus, it provides little insights on the sources of inefficiency and the operational stages where inefficiency may arise. More specifically, with network DEA models, the overall efficiency score θ_j^G of the *j-th* DMUs is the product of the efficiencies estimate $\theta_j^{1,G}$ and $\theta_j^{2,G}$ obtained respectively in the first and in the second stage. Thus, θ_j^G is equal to one only in the case of DMUs fully efficient in each stage. In other cases, if either of the two stages of the public state libraries' production model is inefficient, it will affect the overall efficiency score. According to the efficiency scores we observed,[40] only in MOD_1 there

[33] For further details, see Table A.1 in Appendix A.

[34] Bootstrap procedure is estimated using the software package FEAR 1.15 [56].

[35] The criterion for bandwidth selection follows the plug-in method proposed by Sheather and Jones [44].

[36] As Table 5 shows, the average bias correction (obtained by subtracting the bootstrap bias estimate from the original DEA estimates) is very small. From the perspective of sensitivity analysis, estimated efficiency scores are robust with respect to sampling variation in all models. In fact, using the data on the estimated bias correction and its variance our bootstrap estimates largely accept both the rules set by Simar and Wilson [42] (i.e. the bootstrap algorithm should not be used only if the ratio of the estimated bias correction to its variance is larger that $\frac{1}{\sqrt{3}}$ or, more conservatively, if the estimated bias is less than four times the estimated variance). All the estimates are available from the authors upon request.

[37] The results are not reported here but are available from the authors upon request.

[38] For purposes of comparison and completeness the results under the VRS assumption in MOD_1 are reported in Table A.1 in the Appendix.

[39] In fact, for a given number of DMUs, DEA estimates depends on the number of inputs and outputs in the analysis [38]. This means that, for a given sample size, the reliability of the results from the DEA model depends on the number of input and output variables. For a numerical example of the trade-off between sample size and number of inputs and outputs used for reliability of DEA, see Simar and Wilson [42], p. 439.

[40] Table A.1 in the Appendix reports the efficiency estimates for each library in the sample.

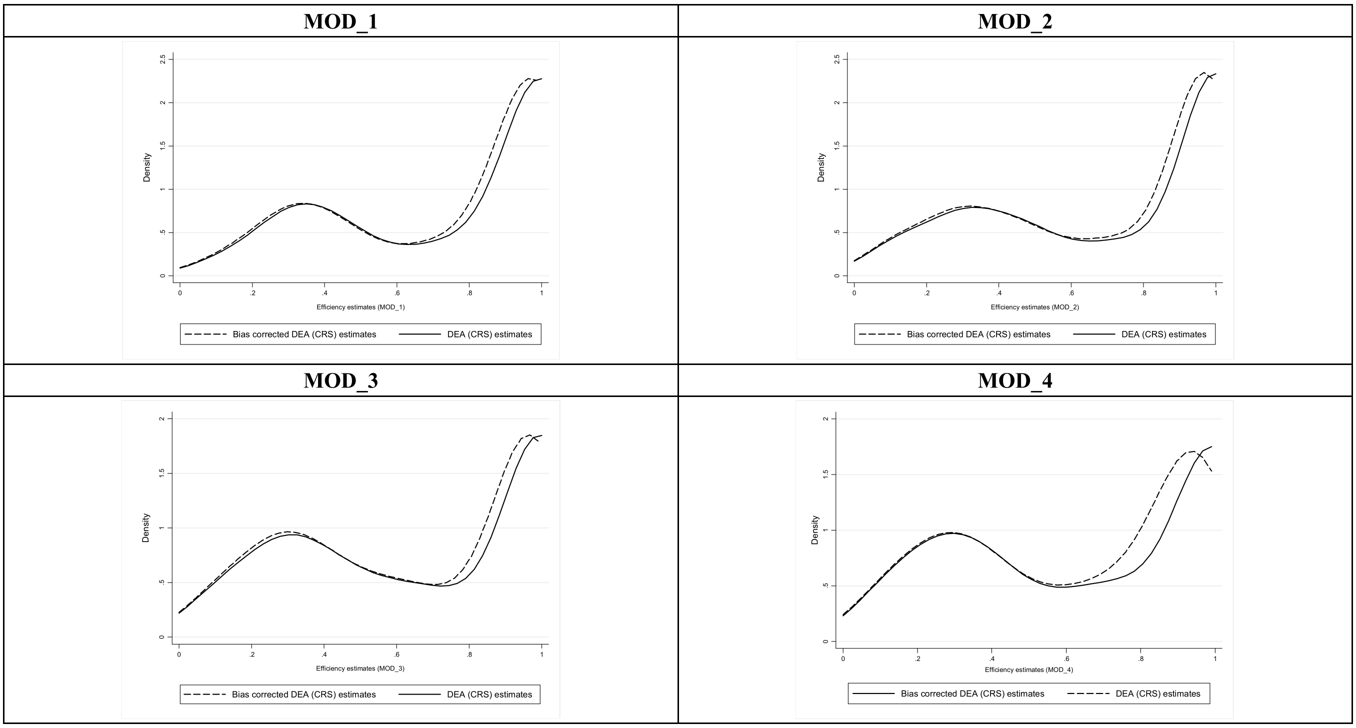

Fig. 3. Kernel density plots. *Source:* our elaboration on data provided by MiBACT Statistical office and RGS. *Note*: Plots show respectively MOD_1, MOD_2, MOD_3 and MOD_4 kernel density estimates under CRS assumption. DEA (CRS) bias corrected scores are estimated with the procedure proposed by Simar and Wilson [6]. Univariate kernel smoothing distribution [43] is estimated through reflection method. The criterion for bandwidth selection followed the plug-in method proposed by Sheather and Jones [44].

Table 6
Statistics of the two-stage network DEA efficiency estimates.
Source: our elaboration on data provided by MiBACT Statistical office and RGS

Models and estimators			Obs.	Mean	St. Dev.	Median	25_p	75_p
MOD_1	NDEA	Overall	44	0.2825	0.2608	0.2460	0.0920	0.3615
		Stage 1	*44*	*0.6909*	*0.2452*	*0.6825*	*0.4968*	*0.9620*
		Stage 2	*44*	*0.4106*	*0.3146*	*0.3510*	*0.1240*	*0.5845*
MOD_2	NDEA	Overall	44	0.1995	0.1836	0.1755	0.0780	0.2360
		Stage 1	*44*	*0.5531*	*0.2729*	*0.5525*	*0.2840*	*0.7590*
		Stage2	*44*	*0.4114*	*0.3105*	*0.3370*	*0.1418*	*0.5915*
MOD_3	NDEA	Overall	44	0.1346	0.1024	0.1075	0.0568	0.1740
		Stage 1	*44*	*0.4304*	*0.2547*	*0.3675*	*0.2493*	*0.5445*
		Stage 2	*44*	*0.4077*	*0.3147*	*0.3430*	*0.1370*	*0.5590*
MOD_4	NDEA	Overall	44	0.1315	0.1016	0.1073	0.0564	0.1735
		Stage 1	*44*	*0.4188*	*0.2434*	*0.3658*	*0.2462*	*0.5435*
		Stage 2	*44*	*0.4047*	*0.3141*	*0.3422*	*0.1365*	*0.5579*

are two libraries that are fully efficient in each stage. In the other models (MOD_2, MOD_3, and MOD_4) none of the DMUs achieves an overall efficiency score of 1.00 (perfectly efficient) because each DMU has an efficiency score smaller than 1 at least in one stage. These results are probably connected to the fact that MOD_2, MOD_3 and MOD_4 do not include variables clearly important for public state library activities. This, indirectly, confirms the robustness of MOD_1.

Finally, in Table 7 we report the pairwise correlation between efficiency estimates. Table 7 shows a clear trade-off between the efficiency levels of conservation and/or improvement of historical collections, on the one side, and, on the other side, the efficiency levels of the use function, which makes collections available to users. Overlapping results are obtained using Spearman and Kendall rank correlations between the efficiency estimates, as reported in Table 8. Consistently with the previous evidence, trade-off emerges between conservation and use functions. That is to say: conservation efficiency tends to be higher for smaller levels of use efficiency.

5.3. Robustness checks for potential outlier

In this Section we provide a robustness check of our previous findings using a subsample of libraries excluding those that show a systematically worse performance. In fact, as we observe in Section 4, using the detection method proposed by Wilson [41] we do not find a single or a small group of DMUs that systematically show a super-efficient coefficient in all models. However, one could argue that our previous findings are due to the presence of worse practices in our sample. Thus, to check for this circumstance we detect three observations that systematically show a worse performance in all the estimated models.[41] To assess if removing these observations affects our empirical findings, we perform a robustness check for the resulting subsample. The results of this exercise is reported in Table 9. Although, as expected, the average efficiency is higher than in the full sample, the picture that emerges from Table 9 largely confirms our previous findings.

In order to further test the robustness of this finding, we have also performed a second robustness check excluding the two National libraries (Rome and Florence) to verify if they might have any advantage or disadvantage in each stage as they compulsorily store all Italian publications.[42] The results of these further estimates are reported in Table 10 and are largely in line with the former. In particular, it is confirmed that on average Italian state libraries perform better in the conservation function that in the use function. Furthermore, these results are quite independent from the different (financial/physical) measures of the collections.

[41] To identify worse practices in our sample we first detect the subsample of DMUs that shows an efficiency score lower that 0.4 in the baseline DEA (CRS) estimates, and then we check if those DMUs are able to perform better in at least one alternative estimator. Those that are not able to perform better are assumed as worse practices. For details see Table A.1 in Appendix A.

[42] We wish to thank an anonymous reviewer for raising this point.

Table 7
Pairwise correlation matrix between efficiency estimates.
Source: our elaboration on data provided by MIBACT Statistical office and RGS

	Models and estimators		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	MOD_1	DEA_CRS	1.000															
(2)		NDEA Overall	0.559	1.000														
(3)		NDEA *Stage 1*	0.114	0.341	1.000													
(4)		NDEA *Stage 2*	0.617	0.883	−0.017	1.000												
(5)	MOD_2	DEA_CRS	0.902	0.616	0.211	0.674	1.000											
(6)		NDEA Overall	0.491	0.773	0.313	0.669	0.541	1.000										
(7)		NDEA *Stage 1*	−0.018	−0.063	0.757	−0.333	0.026	0.293	1.000									
(8)		*Stage 2*	0.624	0.874	−0.029	0.996	0.681	0.678	−0.339	1.000								
(9)	MOD_3	DEA_CRS	0.786	0.701	0.182	0.757	0.870	0.623	−0.031	0.763	1.000							
(10)		NDEA Overall	0.558	0.701	0.296	0.621	0.614	0.864	0.250	0.633	0.709	1.000						
(11)		NDEA *Stage 1*	−0.214	−0.299	0.613	−0.512	−0.173	−0.072	0.767	−0.518	−0.228	0.086	1.000					
(12)		NDEA *Stage 2*	0.612	0.877	−0.025	0.995	0.668	0.664	−0.336	0.992	0.764	0.629	−0.521	1.000				
(13)	MOD_4	DEA_CRS	0.788	0.710	0.132	0.781	0.867	0.626	−0.085	0.788	0.993	0.724	−0.248	0.788	1.000			
(14)		NDEA Overall	0.551	0.702	0.294	0.622	0.605	0.861	0.246	0.632	0.697	0.998	0.092	0.629	0.714	1.000		
(15)		NDEA *Stage 1*	−0.194	−0.292	0.602	−0.506	−0.159	−0.057	0.779	−0.511	−0.224	0.111	0.985	−0.513	−0.243	0.119	1.000	
(16)		NDEA *Stage 2*	0.614	0.877	−0.023	0.995	0.669	0.662	−0.337	0.992	0.765	0.628	−0.516	0.999	0.788	0.628	−0.509	1.000

Note: the table reports the pairwise correlation between efficiency estimates under different model (MOD_1, MOD_2, MOD_3 and MOD_4) using both standard DEA estimator and centralized network DEA estimator proposed by Liang et al. [3] and refined by Kao and Hwang [4].

Table 8
Spearman rank correlation matrix.
Source: our elaboration on data provided by MIBACT Statistical office and RGS

	Models and estimators		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	MOD_1	DEA_CRS	1.000															
(2)		NDEA Overall	0.690	1.000														
(3)		NDEA *Stage 1*	0.061	0.250	1.000													
(4)		*Stage 2*	0.672	0.914	−0.115	1.000												
(5)	MOD_2	DEA_CRS	0.902	0.777	0.154	0.739	1.000											
(6)		NDEA Overall	0.633	0.852	0.266	0.745	0.714	1.000										
(7)		NDEA *Stage 1*	−0.089	−0.061	0.749	−0.350	−0.044	0.249	1.000									
(8)		NDEA *Stage 2*	0.672	0.908	−0.128	0.995	0.740	0.749	−0.350	1.000								
(9)	MOD_3	DEA_CRS	0.746	0.899	0.140	0.849	0.842	0.842	−0.078	0.844	1.000							
(10)		NDEA Overall	0.617	0.820	0.254	0.748	0.688	0.910	0.176	0.753	0.836	1.000						
(11)		NDEA *Stage 1*	−0.231	−0.329	0.600	−0.553	−0.200	−0.041	0.819	−0.557	−0.283	0.014	1.000					
(12)		NDEA *Stage 2*	0.667	0.905	−0.131	0.991	0.733	0.743	−0.353	0.993	0.852	0.753	−0.562	1.000				
(9)	MOD_4	DEA_CRS	0.744	0.892	0.088	0.869	0.838	0.836	−0.116	0.865	0.988	0.853	−0.295	0.871	1.000			
(10)		NDEA Overall	0.621	0.823	0.252	0.758	0.692	0.906	0.164	0.760	0.840	0.997	0.002	0.762	0.855	1.000		
(11)		NDEA *Stage 1*	−0.225	−0.336	0.589	−0.556	−0.205	−0.045	0.816	−0.560	−0.291	0.011	0.995	−0.563	−0.304	0.003	1.000	
(12)		NDEA *Stage 2*	0.672	0.906	−0.129	0.992	0.739	0.740	−0.360	0.992	0.861	0.752	−0.563	0.998	0.882	0.762	−0.565	1.000

Note: the table reports the Spearman's rank correlation coefficient between efficiency estimates under different models (MOD_1, MOD_2, MOD_3 and MOD_4) and using both standard DEA estimator and the centralized network DEA estimator proposed by Liang et al. [3] and refined by Kao and Hwang [4].

Table 9
Efficiency estimates for a subsample of libraries excluding the poorer performer.
Source: our elaboration on data provided by MiBACT Statistical office and RGS

Models and estimators			Obs.	Mean	St. Dev.	Median	25_p	75_p
MOD_1	NDEA	Overall	41	0.3005	0.2612	0.2493	0.1047	0.3663
		Stage 1	41	0.7204	0.2266	0.6979	0.5335	1.0000
		Stage 2	41	0.4317	0.3155	0.3803	0.1433	0.5993
MOD_2	NDEA	Overall	41	0.2117	0.1843	0.1817	0.1047	0.2435
		Stage 1	41	0.5755	0.2690	0.5967	0.3690	0.7871
		Stage2	41	0.4325	0.3109	0.3803	0.1434	0.6268
MOD_3	NDEA	Overall	41	0.1423	0.1016	0.1346	0.0609	0.1817
		Stage 1	41	0.4462	0.2559	0.4023	0.2496	0.5573
		Stage 2	41	0.4284	0.3158	0.3856	0.1429	0.5673
MOD_4	NDEA	Overall	41	0.1402	0.0983	0.1220	0.0609	0.1883
		Stage 1	41	0.4407	0.2427	0.3923	0.2654	0.5478
		Stage 2	41	0.4226	0.3126	0.3856	0.1429	0.5646

Table 10
Efficiency estimates for a subsample of libraries excluding two National libraries (Rome and Florence).
Source: our elaboration on data provided by MiBACT Statistical office and RGS

Models and estimators			Obs.	Mean	St. Dev.	Median	25_p	75_p
MOD_1	NDEA	Overall	42	0.3078	0.2444	0.2861	0.1027	0.3965
		Stage 1	*42*	*0.7573*	*0.2147*	*0.8056*	*0.6452*	*0.9025*
		Stage 2	*42*	*0.4176*	*0.3138*	*0.3258*	*0.1333*	*0.5532*
MOD_2	NDEA	Overall	42	0.2610	0.2004	0.2438	0.0917	0.3396
		Stage 1	*42*	*0.6930*	*0.2755*	*0.7302*	*0.4115*	*0.9742*
		Stage2	*42*	*0.4171*	*0.3039*	*0.3345*	*0.1459*	*0.5754*
MOD_3	NDEA	Overall	42	0.2087	0.1467	0.1787	0.0809	0.3330
		Stage 1	*42*	*0.5875*	*0.2702*	*0.5729*	*0.3429*	*0.8270*
		Stage 2	*42*	*0.4143*	*0.2998*	*0.3552*	*0.1519*	*0.5260*
MOD_4	NDEA	Overall	42	0.2086	0.1466	0.1787	0.0809	0.3330
		Stage 1	*42*	*0.5841*	*0.2701*	*0.5728*	*0.3395*	*0.8270*
		Stage 2	*42*	*0.4160*	*0.2992*	*0.3566*	*0.1519*	*0.5281*

6. Concluding remarks

This study contributes to the literature on the assessment of the efficiency of cultural institutions using a network DEA model to evaluate the efficiency of Italian public state libraries. These are complex organizations that use multiple inputs to produce multiple outputs providing divisible services to the public and conserving ancient books of great historical relevance for future generations. Therefore, they offer an interesting nexus of conservation and use functions, which our approach is able to capture.

In fact, we are able to disentangle different stages of production and to get a closer understanding of the (in)efficiencies of Italian public state libraries. We find that their overall efficiency is low and that they generally perform better in the first stage of conservation, but score poorly in the second stage of use, though caution is needed because of the unavailability of data on digitization and on the online use of these libraries. In face of the widespread complaints about budget cuts, the above analysis would suggest that more ‘value for money’ could be obtained using more efficiently the existing resources because there is room for improving efficiency.

Although our empirical findings are robust with respect to several checks, the conclusions made in this study are still tentative, and several issues remain open to scrutiny. Above all, we remark that our study evaluates library efficiency assuming that environmental factors do not play a role. A different line of reasoning [29,33] suggests that a more appropriate evaluation of the pure efficiency would involve a distinction between service potential and final outcome. In fact, there is often a trade-off between the different objectives of cultural organizations (e.g. conservation vs. use), which makes it difficult to identify the outputs and outcomes affecting the result of the analysis of efficiency. Furthermore, as emphasized by our findings, there is a need for further research and analysis for identifying the role of information technology and further efforts should be dedicated to assess the potential productivity gain in the long run. Finally, the above findings suggest some policy implications. Despite the mission of Italian public state libraries is wide, the importance of the heritage component of their collections is very extensive and, therefore, it inevitably affects their functioning. In fact, the emphasis on conservation is embedded in Italian cultural policy, constituting a priority, at least until recent times. Thus, to foster the use function and to enlarge the audiences of these libraries, clear objectives and a well-defined set of incentives for the staff are needed.

However, for this to work, changes in their organization are required. In fact, Italian public state libraries do not have great autonomy in the management of inputs; they cannot even modify their composition or amount (e.g. they cannot choose the type and the number of staff). Thus, a change in the organization of these institutions would be necessary to improve the performance of libraries and/or to guarantee their survival. Unless these changes occur, any increase in the amount of resources devoted to these libraries would not guarantee an increase in their efficiency.

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Appendix B. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.seps.2018.01.001.

Appendix A

Table A.1
Efficiency estimates.
Source: our elaboration on data provided by MIBACT Statistical office and RGS

DMU	MOD_1						MOD_2				MOD_2				MOD_4			
	DEA			Network DEA			DEA(CRS)	Network DEA			DEA(CRS)	Network DEA			DEA(CRS)	Network DEA		
	CRS	VRS	RTS	Overall	Stage 1	Stage 2		Overall	Stage 1	Stage 2		Overall	Stage 1	Stage 2		Overall	Stage 1	Stage 2
1	0.735	1.000	0.733	0.246	0.446	0.551	0.735	0.171	0.305	0.560	0.733	0.156	0.296	0.528	0.733	0.156	0.296	0.527
2	0.334	1.000	0.329	0.060	1.000	0.060	0.329	0.047	1.000	0.047	0.329	0.047	1.000	0.047	0.210	0.047	1.000	0.047
3	1.000	1.000	1.000	0.826	0.826	1.000	1.000	0.825	0.825	1.000	1.000	0.519	0.519	1.000	1.000	0.516	0.518	0.998
4	1.000	1.000	1.000	0.281	0.698	0.402	1.000	0.221	0.513	0.432	1.000	0.210	0.486	0.432	1.000	0.209	0.485	0.431
5	1.000	1.000	1.000	0.262	0.592	0.443	1.000	0.262	0.592	0.443	1.000	0.148	0.361	0.411	1.000	0.133	0.325	0.410
6	1.000	1.000	1.000	0.442	0.924	0.479	1.000	0.409	0.877	0.466	1.000	0.386	0.827	0.467	1.000	0.384	0.825	0.466
7	0.651	0.658	0.614	0.310	0.692	0.448	0.651	0.310	0.692	0.448	0.614	0.135	0.309	0.436	0.614	0.121	0.308	0.393
8	1.000	1.000	0.992	0.249	1.000	0.249	1.000	0.244	1.000	0.244	0.992	0.244	1.000	0.244	0.992	0.243	1.000	0.243
9	1.000	1.000	1.000	0.202	0.602	0.336	1.000	0.202	0.602	0.336	1.000	0.165	0.492	0.336	1.000	0.148	0.443	0.335
10	1.000	1.000	1.000	0.559	0.906	0.617	1.000	0.386	0.616	0.627	1.000	0.229	0.392	0.583	1.000	0.228	0.392	0.581
11	1.000	1.000	1.000	0.274	0.565	0.484	1.000	0.139	0.263	0.529	1.000	0.110	0.235	0.469	1.000	0.110	0.235	0.468
12	1.000	1.000	1.000	0.304	0.533	0.570	1.000	0.205	0.369	0.556	1.000	0.135	0.238	0.567	1.000	0.134	0.237	0.566
13	0.437	0.445	0.428	0.182	0.707	0.258	0.437	0.182	0.707	0.258	0.428	0.103	0.374	0.276	0.428	0.093	0.373	0.248
14	0.303	0.304	0.303	0.105	0.731	0.143	0.303	0.105	0.731	0.143	0.303	0.077	0.573	0.134	0.302	0.077	0.572	0.134
15	0.726	0.726	0.726	0.271	0.656	0.413	0.726	0.191	0.432	0.442	0.726	0.159	0.359	0.442	0.726	0.143	0.358	0.398
16	0.296	0.461	0.296	0.082	1.000	0.082	0.296	0.046	0.702	0.065	0.296	0.044	1.000	0.044	0.296	0.043	0.709	0.061
17	0.875	1.000	0.866	0.182	1.000	0.182	0.875	0.182	1.000	0.182	0.866	0.182	1.000	0.182	0.866	0.181	1.000	0.181
18	0.107	1.000	0.107	0.039	0.656	0.059	0.107	0.018	0.278	0.066	0.107	0.014	0.557	0.026	0.107	0.014	0.556	0.026
19	0.972	1.000	0.972	0.290	1.000	0.290	0.972	0.290	1.000	0.290	0.972	0.142	0.501	0.283	0.780	0.123	0.436	0.282
20	0.360	0.371	0.320	0.095	0.759	0.125	0.321	0.083	0.597	0.138	0.320	0.073	0.532	0.138	0.320	0.073	0.531	0.137
21	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.705	0.705	1.000	1.000	0.239	0.250	0.956	1.000	0.238	0.249	0.954
22	1.000	1.000	0.192	0.073	1.000	0.073	1.000	0.063	0.907	0.069	0.192	0.046	0.666	0.069	0.190	0.046	0.665	0.069
23	0.268	1.000	0.242	0.055	0.286	0.191	0.245	0.055	0.286	0.191	0.242	0.052	0.265	0.195	0.242	0.051	0.264	0.195
24	1.000	1.000	1.000	0.378	0.564	0.670	1.000	0.286	0.434	0.659	1.000	0.229	0.304	0.753	1.000	0.228	0.303	0.752
25	1.000	1.000	0.541	0.115	0.497	0.232	0.550	0.111	0.478	0.232	0.541	0.061	0.265	0.230	0.541	0.061	0.265	0.229
26	1.000	1.000	0.264	0.052	0.661	0.078	1.000	0.052	0.661	0.078	0.264	0.035	0.602	0.058	0.255	0.035	0.601	0.058
27	1.000	1.000	1.000	0.403	0.673	0.599	1.000	0.180	0.253	0.709	1.000	0.166	0.247	0.673	1.000	0.143	0.212	0.671
28	1.000	1.000	0.598	0.254	0.422	0.602	1.000	0.143	0.221	0.647	0.598	0.105	0.217	0.484	0.598	0.105	0.217	0.483
29	1.000	1.000	1.000	0.870	0.870	1.000	1.000	0.216	0.216	1.000	1.000	0.216	0.216	1.000	1.000	0.215	0.215	1.000
30	0.423	1.000	0.412	0.121	1.000	0.121	0.424	0.116	0.812	0.143	0.412	0.084	0.586	0.143	0.385	0.083	0.585	0.143
31	0.790	1.000	0.706	0.189	0.496	0.380	0.790	0.189	0.496	0.380	0.706	0.166	0.431	0.386	0.706	0.166	0.430	0.385
32	0.296	0.310	0.296	0.037	0.358	0.102	0.296	0.028	0.275	0.102	0.296	0.028	0.275	0.102	0.296	0.028	0.275	0.102
33	0.314	1.000	0.074	0.017	0.221	0.075	0.079	0.013	0.179	0.074	0.074	0.007	0.099	0.074	0.074	0.007	0.099	0.074
34	1.000	1.000	0.180	0.060	0.497	0.121	0.180	0.060	0.496	0.121	0.180	0.059	0.486	0.121	0.180	0.059	0.485	0.121
35	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.156	0.174	0.897	1.000	0.149	0.150	0.994	1.000	0.149	0.150	0.992
36	1.000	1.000	1.000	0.246	0.447	0.551	1.000	0.246	0.447	0.551	1.000	0.223	0.405	0.551	1.000	0.222	0.404	0.550
37	1.000	1.000	1.000	0.838	0.838	1.000	1.000	0.787	0.787	1.000	1.000	0.310	0.310	1.000	1.000	0.306	0.306	1.000
38	0.537	0.725	0.511	0.120	1.000	0.120	0.537	0.120	1.000	0.120	0.511	0.053	0.447	0.119	0.396	0.053	0.446	0.118

39	0.153	1.000	0.102	0.047	0.846	0.055	0.139	0.047	0.846	0.055	0.102	0.042	0.860	0.049	0.096	0.042	0.858	0.049
40	0.468	0.578	0.391	0.083	0.281	0.296	0.468	0.049	0.167	0.296	0.391	0.045	0.154	0.294	0.391	0.045	0.154	0.293
41	1.000	1.000	0.984	0.390	0.390	1.000	1.000	0.127	0.138	0.924	0.984	0.067	0.068	0.984	0.984	0.067	0.068	0.982
42	1.000	1.000	1.000	0.357	0.357	1.000	1.000	0.186	0.186	1.000	1.000	0.103	0.103	1.000	1.000	0.102	0.102	1.000
43	1.000	1.000	1.000	0.366	1.000	0.366	1.000	0.228	0.676	0.338	1.000	0.102	0.290	0.350	0.884	0.101	0.290	0.349
44	0.440	0.450	0.439	0.098	0.403	0.242	0.439	0.096	0.395	0.242	0.439	0.058	0.189	0.307	0.439	0.058	0.188	0.306
Mean	**0.761**	**0.887**	**0.673**	**0.282**	**0.691**	**0.411**	**0.725**	**0.199**	**0.553**	**0.411**	**0.673**	**0.135**	**0.430**	**0.408**	**0.660**	**0.132**	**0.419**	**0.405**

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