ACEI Working Paper Series

IS INNOVATION IN ICT VALUABLE FOR THE EFFICENCY OF ITALIAN MUSEUMS?

Calogero Guccio, Marco Ferdinando Martorana, Isidoro Mazza,

Giacomo Pignataro and Ilde Rizzo

AWP-01-2020 Date: September 2020

Is innovation in ICT valuable for the efficiency of Italian museums?

Calogero Guccio[a], Marco Ferdinando Martorana[a], Isidoro Mazza[a], Giacomo Pignataro[a,b] and Ilde Rizzo[a]

[a] Department of Economics and Business, University of Catania

[b] Department of Management, Economics and Industrial Engineering, Politecnico di Milano

Abstract

This paper investigates the influence of information and communication technologies (ICT) on the efficiency in attracting visitors of Italian museums. Notwithstanding the extensive literature on museum performance measurement, the analysis of the role of technological innovation is relatively neglected. As a first attempt to fill this lacuna, this study presents a two-stage analysis of a novel sample of Italian state-owned museums built by merging information drawn from different sources. In the first stage, we use Data Envelopment Analysis (DEA) and bootstrapping technique to measure the efficiency of museums. In the second stage, we use a bootstrap truncated regression approach to test the extent to which different forms of ICT affect museum efficiency. We distinguish the ICT investments into *in situ* and online services, since the former improve the visitors' experience on site, while the latter can prepare for the visit or, even, be a substitute of the visit. The results reveal that the use of ICT is generally associated with better performances but *in situ* services shows to play a major role.

KEYWORDS: museums; ICT; technological innovation; efficiency; Data Envelopment Analysis; bootstrap truncated regression

JEL classification: C14; C61; I21; Z1

1. Introduction

The continuous improvements and the increasing diffusion of information and communication technology (ICT) have recently contributed to promote innovation in the cultural sector (Borowiecki & Navarrete, 2017). It is generally acknowledged that ICT not only affects supply and demand of cultural goods (Rizzo, 2016), but also modifies the scope and mission of cultural organisations: new sources of economic and cultural value and new business models emerge, while education as well as cultural appreciation and participation are enhanced (Bakhshi & Throsby, 2012). Such aspects are fundamental for museums, which have progressively embraced the use of ICT, though with significant differences across institutions and countries. An interesting issue yet to see is whether the diffusion of technological innovation in museums has indeed contributed to improve their efficiency.

The analysis of technical efficiency of museums has developed remarkably in recent years, and is characterized by a growing use of the frontier techniques (for recent reviews, see: Basso et al, 2018; Guccio et al., 2020a). However, this literature mostly neglects the relationship between ICT advancement and efficiency of cultural institutions (Guccio et al., 2020b). This study aims at contributing to fill this gap by investigating the effects of ICT applications on the technical efficiency of Italian state-owned museums using a two-stage approach: in the first stage, the analysis assesses the ability of museums to utilize resources efficiently for the production of outputs via a bootstrapped DEA (Simar & Wilson, 2000); in the second stage, it evaluates the impact of technological innovation on the estimated technical efficiency, using a boostrap truncated approach (Simar & Wilson, 2007). The study is based on a novel dataset, built by merging information drawn from the statistical office of the Ministry for Heritage, Cultural Activities and Tourism (MIBACT) and from a survey run in 2015 by the Italian National Statistical Office (ISTAT) (ISTAT, 2015). The latter contains over 100 questions, and we focus on those investigating whether and how museums use ICT in the provision of their services, to improve both the accessibility and quality. Results show that ICT services is positively associated with the performances of museums in attracting visitors. In particular, making a distinction between *in situ* and online services, the former play a major role in obtaining this outcome.

The remainder of the paper is structured as follows. Section 2 positions our contribution in the context of the relevant literature. Section 3 presents the methodology, offers a concise description of the institutional setting and describes the data. Section 4 gathers estimates and results. Finally, Section 5 summarizes the main conclusions.

2. Literature review

Museums are cultural institutions devoted to conserve, interpret, research and display heritage (Mairesse & Vanden Eeckaut, 2002). This study refers to two different strands of literature, one investigating the relationship between technological innovation and museums, and another one evaluating the efficiency of museums.

2.1. ICT and museums

Technologies can be used in museums in many ways: apart from standard utilization for administrative purposes (such as word processing, computerised accounting methods, etc.), applications range from diagnostics, conservation and restoration to Information and Communication Technology (ICT). Focusing on the latter, it is worth noting that museums use ICT for a number of functions both *in situ* and online, such as: websites, online ticketing and service information, online access to collections and databases, online exhibitions, mobile applications, virtual reconstructions, interactive kiosks, social media networks or online shopping.

The influence of ICT on museum management has been explored from different disciplinary perspectives, both theoretically and empirically. A common tenet is that ICT and digitization affect the scope and the mission of museums and impact transversally on their activities, modifying conservation and exhibition practices, widening cultural participation and appreciation (Fernandez Blanco & Prieto-

Rodriguez, 2020), and reshaping their role as producers and distributors of cultural content.[1]

Because of technological interactivity, terms such as ‘produsers’, ‘prosumption’ and ‘produsage’ have become popular to describe the evolution in producer/consumer relationships (Bruns, 2013) with implications for museums demand and supply.[2] Moreover, web statistics may offer new opportunities to address the old problem of the revelation of preferences and to orientate museums to meet future users’ needs (Giardina et al., 2016).

It is worth noticing, however, that, notwithstanding the claimed beneficial impact of ICT, the empirical evidence of ICT effects on performance is rather scarce. The implementation of websites is the first and most widespread use of ICT in museums, with different functions, ranging from functional tasks to creations of new cultural experiences. Providing information and facilities for potential visitors to physical museums appears to be prevailing in line with the strategic goal of maintaining a link between the web and the physical site (Pallud, & Straub, 2014). The effectiveness of museums websites in being attractive for visitors with different knowledge about collections cannot be taken for granted and an extensive literature deals with evaluation methods (for a review of evaluation studies, see Kabassi, 2017).

In such a perspective, digitization plays a crucial role because it potentially increases the fruition of collections and involves users actively by allowing the online access to collections. However, museums seem to have a limited attention to information regarding the adoption of digital technology. According to the figures provided by Enumerate Core Survey 4 in Europe,[3] in 2017, on average, only 22%

[1] The different options for managing the access to and the re-use of digital images of museum collections are explored by Bertacchini & Morando (2013).
[2] Contributing content has raised questions of authority (Navarrete, 2013).
[3] Enumerate Core Survey 4 is the fourth edition of a survey monitoring the status of cultural heritage in Europe. 983 institutions belonging to 28 European countries participated to this fourth round. The dataset includes information for each institution in 2017 on: the state of digitisation activity, the dimension and characteristics of collections, digital access, preservation strategy and expenditure. For more information, see: https://pro.europeana.eu/files/Europeana_Professional/Projects/Project_list/ENUMERATE/deliverables/DSI-

of the heritage collections were digital (31% in museums), 54% still needed to be reproduced (57% in museums) and only 36% of digital collections was accessible on line (Nauta et al., 2017),[4] with national libraries being 'front runners' (58%) and museums being quite behind (28%).[5] These figures have to be interpreted with great caution since the sample is not representative and suffers of self-selection bias. Nonetheless, the main findings suggest that cultural heritage institutions are still lagging behind in adopting digital technologies.

Different explanations can be put forward for the partial use of digitization by museums. A political economy explanation might apply when considering that the government has a prominent role in the cultural heritage field and most of the major heritage organizations are somehow publicly funded (Holler & Mazza, 2013). In such a context, the conventional wisdom about the behaviour of heritage experts, such as museum directors, highlights a potential bias in favour of an 'elitist' curatorial approach, due to their educational background and peers' scrutiny. Consistently with this view, communication methods such as ICT and virtual reality may not be adequately appreciated as a tool for the promotion of museum's collections and considered to downgrade the 'high' character of heritage (Peacock & Rizzo, 2008). Paolini et al. (2013) outline that when museums rely on public funding, the relationship with the audience may not be considered a priority and, therefore, the investment in ICT may be limited: one major effect would be the occurrence of a digital divide across countries and institutions, with the consequence that culturally important institutions which are not visible on the Internet may be dominated by less relevant ones.[6]

Another possible explanation for the apparently scarce interest of museums toward the online publication of collections may be due to 'the fear of

2_Deliverable%20D4.4_Europeana_Report%20on%20ENUMERATE%20Core%20Survey%204.pdf

[4] These figures are not weighted. Therefore, the actual percentage of the digitization for cultural heritage in Europe is likely to be even lower than what is shown, since institutions with small collections have the same weight as institutions with large collections.

[5] Online access of metadata is higher but with similar differences: 76% of libraries and 33% of museums have metadata available online for general use.

[6] The issue is quite important for countries like Italy with outstanding heritage distributed across a huge number of sites and museums /institutions.

cannibalization' and the related risk of losing onsite visitors because of their availability online (Navarrete, 2013).[7] However, this does not seem to be the case. Empirical evidence, although scant, would suggest that complementarity - rather than substitution – prevails both with respect to single museums (for Tate Modern, see Bakhshi & Throsby, 2010; for Louvre, see Evrard & Krebs, 2018) and at country level (for United States, see Ateca-Amestoy & Castiglione, 2014). At the same time, while there is no evidence at European level that digitization has extended audiences (Ateca-Amestoy, 2018) it is widely agreed that cultural online access enhances inequalities between socio-economic groups (Krebs, 2012; Mihelj et al., 2019).

The adoption of technological innovation in museums and its effects are likely to depend on their specific features, such as size, governance and degree of autonomy. For example, Camarero et al. (2011) find that larger museums are more likely to engage in technological innovation than small ones. Bertacchini et al. (2018) show that, in Italy, private museums as well as public ones - autonomous, or outsourced - perform better than public museums directly managed by government bodies, as far as web visibility is concerned; similarly, Leva et al. (2019) show that among state museums, the autonomous ones are more active in implementing policies aimed at enhancing accessibility (including ticket on line and facilities through websites), attractiveness (including on-site audio visual equipment for visitors) and relations with the local context (including web advertising).

2.2. Efficiency of museums

The measurement of the efficiency of museums has attracted a growing interest in the last decades. The early works on this topic usually adopted productivity and performance indicators (Weil, 1995) that however have many limitations (Pignataro, 2011). In recent times, the application of non-parametric frontier estimation techniques (mainly the Data Envelopment Analysis – DEA) has become

[7] Digital content from museums can be found at the museum websites, but also in the Google Art Project, Wikipedia, image banks, iTunes and Europeana, as well as in a number of video games, blogs and software applications.

more common. Their use is now well-established due to their flexibility and the fact that they allow for handling production processes involving multiple inputs and outputs. The latter is a critical advantage, given the multifaced nature of museums and the wide range of activities they carry out. Not surprisingly, works in this strand of literature remarkably differ in the set of inputs and outputs chosen as well as in the way museums' "production" process is modelled. In general, among other aspects, museums can be regarded as cultural institutions that preserve and provide access to pieces of art and items of cultural interest, using their staff and physical endowment. Thus, the number of workers and the size of the exhibition area is customarily included among inputs, and the number of visitors among outputs in the large majority of works since the very first applications of non-parametric techniques, and DEA especially, to evaluate museums' efficiency (Pignataro, 2002, Del Barrio et al. 2009). Nevertheless, scholars have tried to deepen the investigation of museums' activities and performance often using a richer set of inputs and outputs as well as more advanced techniques. Among them, Basso & Funari (2004) disentangle visitors according to whether they pay a full-fee or a reduced-fee and consider also temporary exhibitions and other activities among outputs, in their analysis of the efficiency of Italian museums. Similarly, Del Barrio & Herrero (2014) construct indexes related to dissemination and impact of collection as outputs.

A more complex framework to evaluate the efficiency of museums in different activities is the one proposed by Mairesse & Vanden Eeckaut (2002) that uses the Free Disposal Hull (FDH) to run three models, using different sets of outputs to account for preservation, research and communication. Among the inputs they use the opening hours that conversely is included in the output set by Carvalho et al. (2014). On a different perspective, the recent works by Del Barrio-Tellado & Herrero-Prieto (2019) and Guccio et al. (2020a) have exploited the idea that museums activity can be disentangled in two stages and the related distinction between outputs that are under the direct control of the museum's management and those which depend on the operational environment. While the latter paper focuses on the efficiency in the provision of the service potential of museums and estimate the frontier conditional to the environmental factors, Del Barrio-Tellado & Herrero-

Prieto (2019) use a network two-stage DEA to study the overall efficiency of museums.

With the only exception of Taheri &Ansari (2013), including ICT to construct a set of input indexes (which also include information on the size of exhibition area, opening times, different types of workers, facilities, and promotion activities), the link between the diffusion of ICT and museums' efficiency in attracting visitors has been so far neglected, to the best of our knowledge. This is particularly surprising considering the remarkable debate about the use of digital technologies in the field of cultural heritage preservation and promotion.

3. Methods, data and model specification

3.1. Methods

We employ a two-stage non-parametric method to evaluate museums' efficiency and assess the impact of ICT. Specifically, we use a bootstrapped Data Envelopment Analysis (DEA) in the first step to estimate the best-practice frontier and measure museums' efficiency levels (Simar &Wilson, 2000). DEA (Charnes et al., 1978) is a widely used method to assess efficiency of a sample of Decision-Making Units (DMUs). From a technical point of view, DEA allows to compute an efficiency score by solving a linear programming problem for every DMU to identify the nonparametric production frontier; this score represents a radial measure of efficiency computed with respect to the estimated efficient frontier.

As mentioned, a growing number of researchers have adopted DEA to assess the relative performance of museums. There are few reasons for this choice that we follow here. First, non-parametric methods can handle multiple inputs and outputs in a simple manner, while most stochastic approaches require choosing a single output variable. Second, non-parametric approaches do not require assumptions about the functional form or specification of the error term, in contrast to stochastic methods. Furthermore, DEA provides an overall measure of performance that takes the multidimensional nature of museum's performance into account.

Using DEA, the sources of inefficiency can be analysed and quantified for every evaluated unit. We employ an output-oriented model, assuming that museums maximize outputs for given inputs. This choice is rather common in the literature and also preferable in our specification as, in fact, inputs such as the exhibition space and, to some extent, the number of workers are generally fixed, at least in the short run. In formal terms, any efficiency score θ_i, for $i=1, 2, \ldots n$ DMUs, is derived by solving the following linear program, assuming Constant Returns of Scale (CRS) and output orientation:

$$\max_{\theta_i,\lambda} \quad \theta_i \qquad [1]$$

$$\begin{aligned} subject\ to \quad & x_i - \mathrm{X}\lambda \geq 0 \\ & \theta_i y_i - \mathrm{Y}\lambda \leq 0 \\ & \lambda \geq 0 \end{aligned}$$

where λ is a $n \times 1$ vector of variables, X is the matrix of inputs, Y is the matrix of outputs, x_i and y_i are the input and output of *i-th* DMU. The efficiency score θ_i is comprised between 0 and 1. The value 1 characterises the efficient museums, while the lower the efficiency score, the more inefficient is the museum. For an inefficient museum (with $\theta_i < 1$) the value of the variables λ_i allows you to identify a set of efficient museums that constitutes a "best practice" benchmark. Such a museum could improve its efficiency by simultaneously increasing the value of its outputs while using the same amount of inputs, or even less. To account for variable returns to scale (VRS) Banker et al. (1984) add to (1) the convexity constraint $e\lambda = 1$, where e is a row vector with all elements at unity, which allows to distinguish between Technical Efficiency (TE) and Scale Efficiency (SE).

As the deterministic frontier models does not allow for any statistical inference and measurement error, we employ the Simar & Wilson (1998, 2000) bootstrapping procedure, developed to determine statistical properties of DEA estimators, which allows to derive unbiased efficiency scores. The use of bootstrapping techniques is recommended in order to consider a random error model and correct biases and inconsistencies in DEA estimates (Simar & Wilson, 1998; 2000). Furthermore, as the deterministic frontier models are sensitive to outlying and atypical observations, we employ the procedure proposed by Simar (2003). Finally, to improve the robustness of our efficiency assessment, we perform a sensitivity analysis using different nonparametric model specifications and a different subsample.

In addition to knowing the efficiency with which the museums operate, it is interesting for the present study to explain if the use of ICT affects the productive process positively or negatively. Thus, in the second step, we assess the impact of ICT by regressing the efficiency scores θ_i on a vector of explanatory variables (z_i) based on different extent of ICT. The general model in cross-sectional setting is the following:

$$\theta_i = f(z_i) + \varepsilon_i \qquad [2]$$

where ε_i is the error term.

Given that OLS and Tobit estimators would be biased due to the violation of independence between z_i and ε_i, we follow the two-step bias-corrected semi-parametric estimator proposed by Simar &Wilson (2007)[8] that ensures a feasible, consistent inference on the parameters for estimation in the second stage.

3.2. Italian institutional background

We conduct our empirical analysis on a sample of Italian state-owned museums. Italy has a wide and heterogeneous set of museums, which differ as far as institutional features, type of collection, geographical location, and number of visitors are concerned.

According to the survey run by ISTAT (2015) on Italian Museums and Cultural Institutions (*Indagine sui musei e le istituzioni similari*), in Italy there are 4,158 museums, galleries or collections (out of 4,976 total cultural institutions). Among

[8] How to deal with this issue is still an open question in the literature. See, for instance, Simar & Wilson (2007; 2011) Banker & Natarajan (2008), McDonald (2009), Daraio et al. (2018) and Banker et al. (2019).

them, 64.1% are public: 43% belongs to Municipalities while those belonging to the state are only 8.8% of the total.

Museums are dispersed all over the country and are located even in very small Municipalities. Italian museums are also very heterogeneous in terms of type of collection and number of visitors. State museums and similar institutions play a major role, attracting 42.6% of total visitors.

Institutional responsibilities are shared between the state - through the MIBACT - and the decentralized levels. A detailed analysis of the institutional setting is beyond the scope of this paper. Focusing on state museums, it is worth noting that in the last twenty years, as a result of major reforms, some institutions have been granted autonomy. In 1998, four National Museum Poles (*Poli Museali Nazionali*) including the national art galleries and museums in Rome, Venice, Florence and Naples were created, with an autonomous status and a budget. In 2014, a national museum system was established: autonomy and full responsibility for the management of collections was gradually granted, firstly to twenty top museums, monuments and archaeological sites and, two years after, to additional ten museums. On the other hand, all the other less important national non-autonomous museums and heritage sites have been gathered in seventeen regional museum poles (*Poli museali regionali*), under the responsibility of Regional secretariats.

The reform of state museums has been widely debated: while recognizing positive changes in terms of increasing financial autonomy (Unioncamere, 2018), it is also widely agreed that the new organizational model is weak from a managerial perspective. In fact, the management of human resources is still under the control of the ministerial administration (Zan et al., 2018) hindering, therefore, the effective autonomy of museums.

3.3. Data description

We draw data for our empirical excise on Italian state-owned museums from two sources. Data on the relevant inputs and outputs as well as on the use and extent of

ICT are taken from ISTAT (2015), which collects information on all Italian museums and similar institutions for a wide range of topics, including the services provided to visitors, the number of exhibitions and standard proxies for capital and labour. The survey however does not contain information on the number of visitors that we take from a data set provided by the statistical office of the MIBACT.[9]

Given the sensibility of our methodology to the outliers we restrict the full sample originally containing 487 observations, in order to provide a fair efficiency evaluation and avoid problems due to museums' heterogeneity. Specifically, we first exclude monuments and archaeological sites (which have specific characteristics making them hardly comparable to museums) as well as museums included in parks (since the number of visitors cannot be clearly identified) and those museums presenting missing or incomplete data on input and output variables. This first set of checks reduced our initial sample to about 200 museums.

Moreover, observations that, due to errors in the data, are placed on the efficient border could lead to incorrect assessments. Therefore, it is important to detect outliers and treat them properly to avoid increasing sampling noise and distort the results when performing any efficiency assessment. To do so, we apply a method developed by Simar (2003). The resulting final sample of 107 observations is, therefore, quite homogenous for institutional characteristics and features of service provision and virtually free from outliers.

For the first stage analysis of museums efficiency we have followed the main literature in the field that indicate the relevant inputs and outputs characterizing museums' "production" process (Guccio et al., 2020a). Among the different purposes of museums, we focus on the access to the public; thus, we evaluate the efficiency of museums in attracting visitors. To provide more robustness of our efficiency assessment we employ four specifications, differing in the definition of outputs. Table 1 summarizes the input and output variables employed in the models whereas the relative descriptive statistics are gathered in Table 2.

[9] The statistical office of MIBACT provides detailed information regarding museums only for those which are state-owned.

Table 1 around here

Table 2 around here

For inputs, we use in all models the number of workers (*Personnel*) and the available space for exhibitions (*Exhibition_space*), which are widely used in the literature as proxies for capital and labour. Outputs include the total number of visitors (*Visitors*) and the number of temporary exhibitions (*Temp_ex*) in *MOD_1*. The latter variable is used also in *MOD_3* while it is weighted by the number of visitors at the exhibitions in *MOD_2* and *MOD_4*. Museums differ in the ticket policies, as some of them have free entrance and others combine it with entrance fee. We therefore disentangle them in paying (*Visitors_paying*) and not paying (*Visitors_free*) in *MOD_3* and *MOD_4*. Furthermore, to provide robustness to our results we also estimate all our models on the subsample of museums with a mixed entrance policy (free entrance and entrance fee).[10]

Regarding the second stage analysis, we mainly use data derived from the survey run by ISTAT (2015) that we merge with data provided by the MIBACT. The survey run by ISTAT (2015) provides a number of items referring to the services that museums supply, including those related to the use of ICT.

We present the descriptive statistics of ICT services in our sample in Table 3, distinguishing between services provided *in situ*, *i.e.* during the visit, which are aimed at improving the overall cultural experience, and services provided in the website, which are generally accessed before (or independently of) the visit.[11]

[10] For descriptive statistics of the variable in the subsample see table A.1 in the Appendix A.

[11] The values of the ICT variables reflect the museums' answers to the relevant questions of the ISTAT survey. Since all these questions are about the implementation of each service, we build up a set of dummy variables, consistently with the possible answers: YES (we attribute a value of 1) or NO (we attribute a value of 0). A museum could also choose not to answer a question and, therefore, the differences in the number of observations for each variable reflect the different response rates for the different questions. Table A.4 in the Appendix details the distribution of answers for each question.

Table 3 around here

The first type of services includes smartphone and tablet apps, multimedia devices, QRcodes and PC/tablet devices. *In situ* services are active in a percentage of museums not greater than 17.48%, for the availability of multimedia devices, which goes down to about 6.9%, for the availability of PC and tablet devices. Online services are: website, online catalogue, online ticket office, virtual visit, social media accounts, online selling of photos and prints, merchandising, newsletter and community. Services provision ranges from about 64% of museums declaring to have a website, and 52% to have a social media account, to less than 20% for advanced services such as online ticket office, shops and catalogue and virtual visit as well as for the more traditional newsletter and community. A marked variability emerges among museums in the website content and in the implementation of the different ICT services. In order to estimate the impact of ICT, we build for both types of services composite indexes based on the sum of provided services by each museum (see, *infra*, 4.2.).

4. Empirical results

4.1. First stage efficiency estimates

Table 4 shows the main descriptive statistics of the results of the estimation of the four efficiency models, under both assumptions of constant (CRS) and variable returns to scale (VRS)[12] in output-oriented case. The VRS approach assumes that the size of the museums is flexible and that they are able to improve the performance not only by increasing technical efficiency but also by exploiting scale economies. From the bootstrapped results, we can observe that the bias-corrected

[12] The estimates reported in this Section are obtained using the Stata package developed by Badunenko & Mozharovskyi (2016).

estimate is strictly close to the uncorrected estimates and the estimated bias is quite small indicating the consistency of our efficiency assessment.

Table 4 around here

The results in Table 4 show that the average value of efficiency is rather low (depending on the model and scale assumption, in a range between 0.34 and 0.50). A note of caution is in order when making a comparison with results of other studies, both for Italy and for other countries, because of differences in the sample, time period, inputs and outputs considered, but it is quite common to find low values of efficiency of museums.[13] Moreover, the high value of the standard deviation indicates high variability of scores, probably resulting from the residual heterogeneity of museums in the sample, primarily in terms of collection and location and, consequently, of attractivity of visitors.

Additionally, there is some limited variability across the different models, in terms of average efficiency. As expected, MOD_2 and MOD_4 provide, on average, higher efficiency scores, due to the higher number of outputs. In general, however, the efficiency estimates of all the models are highly correlated, as shown by the correlation estimates in Table 5. Thus, in conclusion, the different specification of the production function as well as the assumption on returns to scale do not change the relative performance assessment of museums with respect to the efficiency frontier.

Table 5 around here

[13] A recent study (del Barrio-Tellado & Herrero-Prieto, 2019) on some Spanish museums finds similar average scores.

It is worth mentioning that efficiency estimates are robust also when we perform the analysis on subsample of museums with a mixed entrance policy (free entrance and entrance fee).[14]

We use the bootstrap approach to test the returns to scale characteristics of our sample. This approach provides a statistical indication of which estimator gives more reliable results about the nature of the production technology (Simar and Wilson, 2000). Specifically, we test whether the returns to scale are constant and museums operate under optimal size. We perform the bootstrap test for all proposed model using 2000 replications. In all estimates we find a very low p-value of almost 0.001 for global constant returns to scale, indicating that scale inefficiency appears to be present in the Italian state-owned museums and the majority of DMUs in the sample are not operating at an optimal scale.[15] Thus, the VRS estimates are used in the analysis reported hereafter.

Finally, focusing on the results of one of the four models, specifically MOD_4 estimated under the assumption of variable returns to scale[16], Table 6 shows that the average efficiency for each geographic area varies within a limited range. Moreover, when regressing the efficiency scores on dummies representing the geographic location of museums, none of these geographical dummies is statistically significant (Table 7). In the next section we try to assess the role of ICT in the performance.

Table 6 around here

Table 7 around here

[14] See Tables A.2 and A.3 in the Appendix A.

[15] Results are available from the authors upon request.

[16] There are several reasons to focus on the results of just MOD_4, estimated under the assumption of variable returns to scale. First, the very high correlation among the different models. Second, the more refined definition of both outputs provided by this model, due to the differentiation of the number of visitors between paying and non-paying ones, and to the weighting of the number of temporary exhibitions by the number of their visitors. In this way, the efficiency scores are the least penalizing for each museum, among the four models.

4.2. Second stage analysis: the estimation of the impact of ICT on museums' efficiency

We will now explore the issue of whether and at which extent the ICT services provided by museums have an impact on the differences in their efficiency, as estimated in the previous sections. In particular, we will regress the efficiency scores of each museum on a set of variables representing the different ICT services.[17]

Following the questions included in ISTAT (2015), we can represent the ICT 'effort' of Italian museums along different dimensions. We differentiate the ICT investment on *in situ* services from the realization of online services since the former mainly aim to improve the visitors' experience on site, while the latter prepare for - or stimulate - the visit or, eventually, be a substitute of the visit. In addition, we further ascertain whether a museum has implemented different services for each category of services.[18]

We also build up a summary index for each category of ICT services, simply as the sum of values recorded for each dummy variable, within each of the two categories of services, on the basis of the YES/NO answers to the survey questions. The maximum potential value of the index for the *in situ* services is, therefore, equal to 4 (even if, in the sample, the maximum number of recorded services reached is 3 for one missing answer), while, for the online services, the maximum potential value is 9 (8 in the sample).[19] As a consequence of the low values recorded for each single service, the average values of the composite indices are low and, again, with a high variability across the different museums.

Turning, now, to the research question about whether the ICT effort of museums affect their efficiency, we consider the efficiency values estimated according to

[17] The descriptive statistics of the employed second stage variables are reported in Table 3.
[18] Their features and distribution have been described in detail *supra*, at the end of 3.3 .
[19] For the *online* services the number of observations for which the composite index is computed drops to 92, since this is the number of museums that have filed a YES/NO answer to each of the 9 relevant questions.

MOD_4, under the assumption of variable returns to scale.[20] We estimate the impact of the different ICT variables, according to different models. In particular, we estimate three different sets of models. The first one considers, as regressors, all the single ICT variables: we run two separate regressions, one with all the variables for the *in situ* services and the other with all the variables for the online services. Moreover, for each of these two estimates, we also run an additional regression with the same set of variables and controlling for whether museums allow for free entrance. In such a way, we can take into account the potential effect of free entrance on the number of visitors of a museums and its efficiency (since the number of visitors is regarded as a measure of its outputs), avoiding in this way improper attributions of this effect to the existence of the different ICT services.

The second set of estimates include models where the impact of ICT services is considered separate for each single service. Since the ICT services are generally provided jointly, and their measures are highly correlated, these set of estimates, in which the variables representing the ICT services are introduced one by one, may avoid the estimation bias potentially arising from the correlation of the variables.

Finally, the third set of estimates include the ICT variables through the composite indices: we run an estimate of the impact of the composite index of only *in situ* services, one with the index of only the *online* services and another one with both. Moreover, as before, we run three additional estimates, controlling for free entrance.

In general, we expect that the existence of *in situ* services, improving the quality of the experience at a museum, will attract more visitors and, therefore, can potentially improve the efficiency of a museum. As for the online services, the expected potential effect on efficiency may be ambiguous since these services can either stimulate visits to a museum or be a substitute for the visit.

All estimates are obtained with the bootstrap truncated algorithm proposed by Simar and Wilson (2007). We computed 2000 bootstrap iterations, showing here

[20] The other estimated models with results largely overlapping those reported here. The results of these additional exercises are available upon request.

the mean, the standard deviation and the significance of the coefficients for each variable. The estimates are obtained using the Stata package developed by Badunenko & Tauchmann (2019).

Table 8 reports the results of the first set of estimates, including the regressions with all the variables representing the ICT services (separately for the *in situ* and for the online services).

Table 8 around here

The results show that, independently of the model estimated, the only significant effect is observed for the applications for tablets and smartphones, among the *in situ* services, and for the online catalogue, among the online services. The variables representing the website and the photo and print shop are weakly significant. For all the significant variables, the observed coefficient is positive. While this is the expected outcome for the *in situ* services, this result for the online services show that they are reinforcing the number of visitors and are not to be interpreted as a substitute for the visit.

Very similar results are obtained when regressions are run, introducing the ICT variables one by one, as shown in Table 9.

Table 9 around here

Finally, Table 10 reports the results for the third set of estimates, the one with the ICT services represented by the composite indices.

Table 10 around here

When the ICT services are represented with a summary index of each category, the only significant category is the one of the *in situ* services. This result complements the previous ones considering a more “analytical” impact of ICT, and provides a test of the relative strength of the two categories of services, in terms of their ability to improve the efficiency of museums in attracting visitors.

5. Concluding remarks

There are several reasons why ICT services, here described, can be useful to increase the performance of museums in attracting visitors. Information available on the website can provide useful information to prepare or stimulate the visit. Other ICT services, provided in the museum itself, can improve the experience of the visitor. The recent pandemic has put an important spotlight on ICT showing the crucial importance of technology – unforeseen to this extent - as source of remedies for keeping alive the activity of the institutions as well as the attention of the visitors.

Several studies have investigated the adoption of new ICT services by museums, addressing how these can affect management and demand, and even determine new forms of interaction between suppliers and consumers. However, they have neglected the relationship between ICT and museum efficiency. This is further remarkable because there is a growing literature investigating the efficiency of museums.

This study is the first attempt to bridge the gap between the investigation on ICT applications and efficiency analysis. It investigates efficiency in terms of the ability of museums to attract visitors, using a novel data set, merging recent information on supply and demand concerning provided by two main Italian sources, ISTAT and MIBACT. Due to the wide heterogeneity of the museums regarding, among others, their ownership, management, size, type of collection, we have been very cautious and reduced the original data set to a rather homogeneous sample of Italian state-owned museums. The empirical analysis shows that the presence of ICT services – both *in situ* and online - is associated with higher efficiency of museums, but that is true for a limited number of services. This outcome contradicts the claim that information on the web is a substitute for physical visits. It also shows that ICT services are not *the* solution to the problem of improving efficiency. Some services do not show to have significant effect. Moreover, among those that do have a positive relationship with efficiency, *in situ* services are relative more influent on efficiency.

Future research is needed why some services are more successful than others in attracting visits. This is a broad problem that requires a multidisciplinary approach. For example, it would be interesting to investigate if private management can be more innovative than the public one in improving efficiency through the adoption of ICT services and whether there can be political economic reasons, probably connected to a specific institutional framework of a country. In such a perspective, it might be also interesting to investigate whether the size of museums and/or the type of collections (for instance, archaeological, fine arts, ethnographical, etc) matter. From the demand side, the study of visitors' behaviour could be helpful in guiding the selection and implementation of ICT services to the purpose of improving efficiency. Useful research insights might also derive by the use of Web Analytics and users generated content.

References

Ateca-Amestoy, V., and Castiglione, C. (2014). *Live and Digital Engagement with the visual arts.* Paper presented at the 18th International Conference on Cultural Economics, Université du Québec, Montreal.

Badunenko, O., & Mozharovskyi, P. (2016). Nonparametric frontier analysis using Stata. *The Stata Journal,* 16(3), 550–589.

Badunenko, O., & Tauchmann, H. (2019). Simar and Wilson two-stage efficiency analysis for Stata. *The Stata Journal,* 19(4), 950-988.

Bakhshi, H., & Throsby, D. (2010). *Culture of Innovation. An economic analysis of innovation in arts and cultural organisations*. Nesta Report, London.

Bakhshi, H., & Throsby, D. (2012). New technologies in cultural institutions: theory, evidence and policy implications, *International Journal of Cultural Policy*, 18(2), 205-222.

Banker R.D., Charnes A., & Cooper W.W. (1984), Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30,1078–1092.

Banker R.D., & Natarajan R. (2008), Evaluating contextual variables affecting productivity using data envelopment analysis. *International Journal of Operational Research*, 56(1), 48–58.

Banker, R., Natarajan, R., & Zhang, D. (2019). Two-stage estimation of the impact of contextual variables in stochastic frontier production function models using data envelopment analysis: second stage OLS versus bootstrap approaches. *European Journal of Operational Research*, 278(2), 368-384.

Bertacchini, E., Dalle Nogare C., & Scuderi, R. (2018). Ownership, organization structure and public service provision: the case of museums. *Journal of Cultural Economics*, 42(4), 619-643.

Bertacchini, E., & Morando, F. (2013). The future of museums in the digital age: New models for access to and use of digital collections. *International Journal of Arts Management*, 15(2), 60-72.

Basso, A., & Funari, S. (2004). A quantitative approach to evaluate the relative efficiency of museums. *Journal of Cultural Economics,* 28(3), 195-216.

Basso, A., Casarin, F. & Funari, S. (2018). How well is the museum performing? A joint use of DEA and BSC to measure the performance of museums. *Omega*, 81, 67-84.

Bodo, C., & Bodo, S. (2016). Country profile: Italy. In Council of Europe/ERICarts, Compendium of Cultural Policies and Trends in Europe", 18th edition. Available under: <http:// www.culturalpolicies.net>. ISSN: 2222-7334.

Borowiecki, K. J., & Navarrete, T. (2017). Digitization of heritage collections as indicator of innovation. *Economics of Innovation and New Technology*, 26(3), 227–246.

Bruns, A. (2013). From prosumption to produsage. In: Towse, R., & Handke, C. (Eds.), *Handbook on the digital creative economy*. Edward Elgar Publishing, Cheltenham, 67-78.

Camarero, C., Garrido, M. J., & Vicente, E. (2011). How cultural organizations' size and funding influence innovation and performance: the case of museums. *Journal of Cultural economics*, *35*(4), 247.

Carvalho, P., Costa, J. S., & Carvalho, A. (2014). The economic performance of Portuguese museums. *Urban Public Economics Review,* 20, 12-37.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6), 429–444.

Daraio, C., Simar, L., & Wilson, P. W. (2018). Central limit theorems for conditional efficiency measures and tests of the 'separability' condition in non-parametric, two-stage models of production. *The Econometrics Journal*, 21(2), 170-191.

Del Barrio, M.J., Herrero, L.C., & Sanz, J.A. (2009). Measuring the efficiency of heritage institutions: a case study of a regional system of museums in Spain. *Journal of Cultural Heritage*, 10(2), 258–268.

Del Barrio, M.J., & Herrero, L.C. (2014). Evaluating the efficiency of museums using multiple outputs: evidence from a regional system of museums in Spain. *International Journal of Cultural Policy*, 20(2), 221-238.

Del Barrio-Tellado, M. J., & Herrero-Prieto, L.C. (2019). Modelling museum efficiency in producing inter-reliant outputs. *Journal of Cultural Economics*, 43(3), 485-512.

Evrard, Y., & Krebs, A. (2018). The authenticity of the museum experience in the digital age: the case of the Louvre. *Journal of Cultural Economics*, 42(3), 353-363.

Fernandez-Blanco, V., & Prieto-Rodríguez, J. (2020). Museums. In: Towse, R., & Hernández, T. N. (Eds.), *Handbook of Cultural Economics, Third Edition*. Edward Elgar Publishing, Cheltenham.

Giardina, E., Mazza, I., Pignataro, G. & Rizzo, I. (2016). Voluntary Provision of Public Goods and Technology. *International Advances in Economic Research*, 22, 321–332.

Guccio, C., Martorana, M., Mazza, I., Pignataro G. and Rizzo, I. (2020a). *An analysis of the productive efficiency of Italian museums using a generalised conditional efficiency model*. Socio-economic Planning Sciences, forthcoming

Guccio, C., Martorana, M., Mazza, I., & Rizzo, I. (2020b). Back to the Future: Does the use of information and communication technology enhance the performance of public historical archives? *Journal of Cultural Economics*, published online on 03-25-20. https://doi.org/10.1007/s10824-020-09385-1

Holler, M. J., & Mazza, I. (2013) Cultural heritage: public decision-making and implementation. In: Rizzo, I. & Mignosa, A. (eds.) *Handbook on the economics of cultural heritage*. Edward Elgar, Cheltenham, 17–36.

ISTAT (2015). *Indagine sui musei e le istituzioni similari: Microdati ad uso pubblico*. Roma: ISTAT. https://www.istat.it/it/archivio/167566

Kabassi, K. (2017). Evaluating websites of museums: State of the art. *Journal of Cultural Heritage*, 24, 184-196.

Krebs, A. (2012) *Education and access to digital culture: the current situation and future directions for European culture.* http://www.houseforculture.eu/upload/Docs%20ACP/ 581educationdigitalencatcannekrebsENGL.pdf.

Leva, L., Menicucci, V., Roma, G., & Ruggeri, D. (2019). *Innovazioni nella governance dei musei statali e gestione del patrimonio culturale: alcune evidenze da un'indagine della Banca d'Italia*, Questioni di Economia e Finanza, n. 525.

Mairesse, F., & Vanden Eeckaut, P. (2002). Museum assessment and FDH technology: towards a global approach. *Journal of Cultural Economics*, 26(4), 261–286.

McDonald J. (2009). Using least squares and tobit in second stage dea efficiency analyses, *European Journal of Operational Research* 197 (2), 792–798

Mihelj, S., Leguina, A., & Downey, J. (2019). Culture is digital: Cultural participation, diversity and the digital divide. *New Media & Society*, *21*(7), 1465-1485.

Navarrete, T. (2013), Museums in: Towse, R. & Handke, C. (eds.), *Handbook on the digital creative economy*. Edward Elgar Publishing, Cheltenham, 330-343

Nauta, G.J., van den Heuvel, W., & Teunisse, S. (2017). *Report on ENUMERATE Core Survey 4*, Europeana. https://pro.europeana.eu/files/Europeana_Professional/Projects/Project_list/ENUMERATE/deliverables/DSI-2_Deliverable%20D4.4_Europeana_Report%20on%20ENUMERATE%20Core%20Survey%204.pdf

Pallud, J., & Straub, D. W. (2014). Effective website design for experience-influenced environments: The case of high culture museums. *Information & Management*, 51(3), 359-373.

Paolini, P., Mitroff Silvers, D., & Proctor N. (2013), Technologies for cultural heritage. In: Rizzo, I., & Mignosa, A. (eds.) *Handbook on the economics of cultural heritage*. Edward Elgar Publishing, Cheltenham, 272-289.

Peacock, A.T. & Rizzo, I. (2008) *The heritage game. Economics, policy and practices*. Oxford University Press, Oxford.

Pignataro, G. (2002). Measuring the efficiency of museums: a case study in Sicily. In Rizzo, I., & Towse, R., (eds.), *The economics of heritage: a study in the political economy of culture in Sicily*. Edward Elgar Publishing, Cheltenham, 65–78.

Pignataro, G. (2011). Performance indicators. In Towse, R. (ed.), *A handbook of cultural economics. Second edition*. Edward Elgar Publishing, Cheltenham, 332-338

Rizzo, I. (2016), Technological Perspectives for Cultural Heritage, in: Rizzo, I. and Towse, R. (eds.), *The Artful Economist*. Springer International Publishing, 197-214.

Simar, L. (2003), Detecting Outliers in Frontier Models: A Simple Approach, *Journal of Productivity Analysis*, 20, 391–424.

Simar, L., & Wilson, P. W. (1998). Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. *Management Science* 44(1), 49–61

Simar L, & Wilson P. W. (2000). Statistical inference in nonparametric frontier models: the state of the art. *Journal of Productivity Analysis*. 13(1), 49–78.

Simar, L., & Wilson, P. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics*, 136(1), 31–64.

Simar, L., & Wilson, P. W. (2011). Two-stage DEA: caveat emptor. *Journal of Productivity Analysis*, 36(2), 205.

Taheri, H., & Ansari, S. (2013). Measuring the relative efficiency of cultural-historical museums in Teheran: DEA approach. *Journal of Cultural Heritage*, 14 (5), 431-438.

Unioncamere (2018). Io sono cultura, Quaderni di Symbola, Rome.

Weil, S. E. (1995). Performance indicators for museums: Progress report from wintergreen. *The Journal of Arts Management, Law, and Society,* 23(4), 341–351.

Zan, L., Bonini Baraldi, S., & Santagati, M.E. (2018) Missing HRM: the original sin of museum reforms in Italy. Museum management and curatorship, 33 (6), 530-545.

TABLES AND FIGURES

Table 1. Estimated efficiency models

Variable name	Description	MOD_1	MOD_2	MOD_3	MOD_4
	Inputs				
Personnel	No. of workers	X	X	X	X
Exhibition space	Available space for exhibitions in square meters	X	X	X	X
	Outputs				
Visitors	No. of total visitors	X	X		
Visitors_paying	*No. of visitors paying entrance fee*			X	X
Free visitors	*No. of visitors with free entrance*			X	X
Temp_ex	No. of temporary exhibitions	X		X	
W_temp_ex	No. of temporary exhibitions weighted by no. of visitors		X		X

Source: our elaboration on data provided by ISTAT and by MIBACT

Table 2. Sample statistics of inputs and outputs variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
Personnel	107	18.64	17.58	1.00	90.00
Exhibition space	107	1227.11	1480.03	90.00	10000.00
Visitors	107	14731.53	14769.25	1282.00	74406.00
Visitors_paying	107	4894.88	8043.28	0.00	41424.00
Free visitors	107	9836.65	8400.64	1282.00	42512.00
Temp_ex	107	1.90	3.86	0.00	30.00
W_temp_ex	107	4661.34	10439.02	0.00	74406.00

Source: our elaboration on data provided by ISTAT and by MIBACT

Table 3. Sample statistics of second stage analysis

Variable	Answer	Mean	Std. Dev.	Min	Max
		In situ services			
Smartphone and tablet apps	102	0.1078	0.3102	0.0000	1.0000
Multimedia devices	103	0.1748	0.3798	0.0000	1.0000
QRcode	102	0.1176	0.3222	0.0000	1.0000
PC and tablet devices	102	0.0686	0.2528	0.0000	1.0000
		Online services			
Website	101	0.6436	0.4813	0.0000	1.0000
Online catalogue	99	0.1010	0.3013	0.0000	1.0000
Online ticket office	98	0.0714	0.2575	0.0000	1.0000
Virtual visit	98	0.1224	0.3278	0.0000	1.0000
Social media	99	0.5253	0.4994	0.0000	1.0000
Photo and prints shop	96	0.1667	0.3727	0.0000	1.0000
Merchandising	95	0.0632	0.2432	0.0000	1.0000
Newsletter	97	0.0515	0.2211	0.0000	1.0000
Web community	96	0.1146	0.3185	0.0000	1.0000
		Composite index			
In situ services index	*102*	*0.4608*	*0.8043*	*0.0000*	*3.0000*
Online services index	*92*	*1.1630*	*1.3850*	*0.0000*	*8.0000*

Source: our elaboration on data provided by ISTAT and by MIBACT

Table 4. Efficiency estimates - full sample

Model	Obs	Uncorrected efficiency scores		Bias-corrected efficiency scores		
		Mean	Std. Dev.	Mean	Std. Dev.	Bias
MOD_1 (CRS)	107	0.3440	0.2825	0.3369	0.2791	0.0071
MOD_1 (VRS)	107	0.4335	0.2910	0.4283	0.2875	0.0052
MOD_2 (CRS)	107	0.4331	0.2942	0.4279	0.2907	0.0052
MOD_2 (VRS)	107	0.5014	0.2974	0.4813	0.2855	0.0201
MOD_3 (CRS)	107	0.3476	0.2885	0.3434	0.2850	0.0042
MOD_3 (VRS)	107	0.4400	0.2968	0.4347	0.2932	0.0053
MOD_4 (CRS)	107	0.4337	0.2958	0.4207	0.2922	0.0130
MOD_4 (VRS)	107	0.4963	0.3014	0.4913	0.2978	0.0050

Source: our elaboration on data provided by ISTAT and by MIBACT

Table 5. Correlation between efficiency estimates in the employed models – full sample

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	MOD_1 (CRS)	1.0000							
(2)	MOD_1 (VRS)	0.8479	1.0000						
(3)	MOD_2 (CRS)	0.9211	0.7986	1.0000					
(4)	MOD_2 (VRS)	0.8228	0.9336	0.8859	1.0000				
(5)	MOD_3 (CRS)	0.9168	0.8155	0.8503	0.8028	1.0000			
(6)	MOD_3 (VRS)	0.8264	0.9881	0.7941	0.9372	0.8392	1.0000		
(7)	MOD_4 (CRS)	0.8680	0.7999	0.9326	0.8744	0.9368	0.8285	1.0000	
(8)	MOD_4 (VRS)	0.8107	0.9347	0.8597	0.9898	0.8279	0.9519	0.8872	1.0000

Source: our elaboration on data provided by ISTAT and by MIBACT

Table 6. Efficiency estimates by geographical area – full sample

Macroarea	Obs.	Mean	Std. Dev.	Min	Max
North-West	4	0.590	0.433	0.148	1.000
North-East	14	0.556	0.363	0.035	1.000
Centre	46	0.476	0.296	0.108	1.000
South	39	0.477	0.279	0.099	1.000
Islands	4	0.615	0.306	0.265	1.000
Full sample	**107**	**0.496**	**0.301**	**0.035**	**1.000**

Source: our elaboration on data provided by ISTAT and by MIBACT

Table 7. Testing for efficiency differences between museum located in different geographical area – full sample

Macroarea	Estimates
North-West	0.118 (0.145)
North-East	0.164 (0.255)
South	0.196 (0.182)
Islands	0.003 (0.097)
Constant	0.372*** (0.073)
Obs.	107

Source: our elaboration on data provided by ISTAT and by MIBACT
Note: The Table reports double bootstrap truncated estimates (n=2000, Algorithm 2), proposed by Simar and Wilson (2007). The omitted variable is Centre

Table 8. Results for Bootstrap Truncated Two-Stage Estimates - all ICT services

Variables	(1)	(2)	(3)	(4)
In situ services				
Smartphone and tablet apps	0.205* (0.120)		0.291*** (0.112)	
Multimedia devices	0.014 (0.092)		0.074 (0.077)	
QRcode	-0.004 (0.103)		0.009 (0.086)	
PC/tablet devices	-0.080 (0.139)		0.042 (0.127)	
Online services				
Website		0.128* (0.068)		0.125* (0.066)
Online catalogue		0.298** (0.148)		0.345** (0.147)
Online ticket office		0.288 (0.196)		0.236 (0.189)
Virtual visit		0.171 (0.147)		0.174 (0.145)
Social media		-0.025 (0.095)		-0.034 (0.096)
Photo and prints shop		0.242* (0.145)		0.245* (0.145)
Merchandising		-0.155 (0.301)		-0.156 (0.301)
Newsletter		0.041 (0.312)		0.026 (0.309)
Community		0.031 (0.202)		0.037 (0.199)
Entrance policy				
Free entrance dummy			-0.116 (0.072)	-0.049 (0.069)
Constant	0.375*** (0.069)	0.338*** (0.039)	0.388*** (0.062)	0.356*** (0.041)
Obs	102	94	102	94

** Significant at 10 %; ** significant at 5 %; *** significant at 1 %. Standard errors are reported in parenthesis.*
Notes: Table report double bootstrap truncated estimates (n=2000, Algorithm 2), proposed by Simar and Wilson (2007).
Source: our elaboration on data provided by ISTAT and by MIBACT

Table 9. Second stage estimates including variables on ICT services one by one

Variables	Estimated coefficient	Constant	Obs
	In situ services		
Smartphone and tablet apps	0. 192* (0.106)	0.346 *** (0.040)	102
Multimedia devices	0.067 (0.087)	0.354*** (0.042)	103
QRcode	0.030 (0.106)	0.359*** (0.042)	102
PC/tablet devices	0.020 (0.133)	0.362*** (0.041)	102
	Online services		
Website	0.135* (0.074)	0.371*** (0.041)	101
Online catalogue	0.351** (0.154)	0.356*** (0.057)	99
Online ticket office	0.327* (0.201)	0.370*** (0.050)	98
Virtual visit	0.112 (0.119)	0.349*** (0.037)	98
Social media	0.019 (0.067)	0.352*** (0.033)	99
Photo and prints shop	0.037 (0.099)	0.353*** (0.034)	96
Merchandising	0.087 (0.162)	0.352*** (0.035)	95
Newsletter	0.169 (0.195)	0.372*** (0.051)	97
Community	0.082 (0.142)	0.374*** 0.045)	96

** Significant at 10 %; ** significant at 5 %; *** significant at 1 %. Standard errors are reported in parenthesis.*
Notes: Table report double bootstrap truncated estimates (n=2000, Algorithm 2), proposed by Simar and Wilson (2007). Each row in the table represents a different estimate
Source: our elaboration on data provided by ISTAT and by MIBACT

Table 10. Second stage estimates – composite indexes

Variables	(1)	(2)	(3)	(4)	(5)	(6)
In situ services index	0.086* (0.045)		0.076* (0.040)	0.081** (0.034)		0.077** (0.035)
Online services index		0.007 (0.032)	0.016 (0.031)		0.011 (0.032)	0.015 (0.033)
			Entrance policy			
Free entrance dummy				-0.030 (0.104)	-0.049 (0.069)	-0.096 (0.076)
Constant	0.397*** (0.093)	0.339*** (0.056)	0.323*** (0.067)	0.396*** (0.093)	0.340*** (0.055)	0.324*** (0.066)
Obs	102	94	92	102	94	92

** Significant at 10 %; ** significant at 5 %; *** significant at 1 %. Standard errors are reported in parenthesis.*
Notes: Table report double bootstrap truncated estimates (n=2000, Algorithm 2), proposed by Simar and Wilson (2007).
Source: our elaboration on data provided by ISTAT and by MIBACT

APPENDIX A

Table A.1. Sample statistics of inputs and outputs variables in subsample with mixed entrance (with and without fee).

Variable	Obs	Mean	Std. Dev.	Min	Max
Personnel	58	23.38	18.85	1.00	90.00
Exhibition space	58	1644.50	1823.14	115.00	10000.00
Visitors	58	20079.55	17239.30	2514.00	74406.00
Visitors_paying	58	9030.21	9072.53	663.00	41424.00
Free visitors	58	11049.34	9114.12	1445.00	42512.00
Temp_ex	58	2.16	4.77	0.00	30.00
W_temp_ex	58	7278.97	13477.09	0.00	74406.00

Source: our elaboration on data provided by ISTAT and by MIBACT

Table A.2 Efficiency estimates – subsample with mixed entrance (with and without fee).

Variable	Obs.	Uncorrected efficiency scores		Bias-corrected efficiency scores		
		Mean	Std. Dev.	Mean	Std. Dev.	Bias
MOD_1 (CRS)	58	0.3589	0.2936	0.3481	0.2930	0.0108
MOD_1 (VRS)	58	0.5095	0.3084	0.4993	0.3078	0.0102
MOD_2 (CRS)	58	0.4052	0.3048	0.3971	0.3042	0.0081
MOD_2 (VRS)	58	0.5356	0.3144	0.5302	0.3138	0.0054
MOD_3 (CRS)	58	0.3770	0.3025	0.3582	0.3019	0.0189
MOD_3 (VRS)	58	0.5188	0.3153	0.4877	0.3147	0.0311
MOD_4 (CRS)	58	0.4215	0.3099	0.4046	0.3093	0.0169
MOD_4 (VRS)	58	0.5424	0.3181	0.5153	0.3175	0.0271

Source: our elaboration on data provided by ISTAT and by MIBACT

Table A.3 Correlation between efficiency estimates in full and subsample – Model 4

		(1)	(2)	(3)	(4)
(1)	MOD4_CRS	1.0000			
(2)	MOD4_CRS_S	0.9851	1.0000		
(3)	MOD4_VRS	0.8393	0.8174	1.0000	
(4)	MOD4_VRS_S	0.7998	0.8053	0.9547	1.0000

Source: our elaboration on data provided by ISTAT and by MIBACT

Table A.4. Extent of ICT services.

Service	Obs	Answer		
		Yes	**No**	**No answer**
		In situ services		
Smartphone and tablet apps	107	11	91	5
Multimedia devices	107	18	85	4
QRcode	107	12	90	5
PC/tablet devices	107	7	95	5
		Online services		
Website	107	65	36	6
Online catalogue	107	10	89	8
Online ticket office	107	7	91	9
Virtual visit	107	12	86	9
Social media	107	52	47	8
Photo and prints shop	107	16	80	11
Merchandising	107	6	89	12
Newsletter	107	5	92	10
Community	107	11	85	11

Source: our elaboration on data provided by ISTAT