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BACK TO THE FUTURE. THE EFFECT OF DIGITAL TECHNOLOGY ON THE PERFORMANCE OF PUBLIC HISTORICAL ARCHIVES

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Back to the Future. The effect of digital technology on the performance of public historical archives

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Abstract

The diffusion of social media platforms in public services calls for investigating their role in terms of supply and consumption. In cultural heritage, the application of such technologies has manifold implications ranging from preservation, to production and usage of cultural goods. This paper explores the scope for the use of new media in cultural heritage using website services. More specifically, we investigate the efficiency of public historical archives (PHAs) in Italy over the period 2009-2014 and try to assess the influence of websites on their efficiency. We use a two-stage approach involving the estimation of the frontier using Data Envelopment Analysis (DEA) and Window DEA (WDEA) to obtain PHAs efficiency scores and evaluate the effect of the use of websites on efficiency.

Keywords: Innovation; Public services; Cultural heritage; Archives; Non parametric frontier

JEL Classification: Z1; D24.

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1. Introduction

The performance of the public sector has become a major concern in recent decades. The continuous improvements and fast-growing diffusion of digital technology (DT) allows for its extensive use in the management of public services in various sectors (health, education, cultural heritage, etc.), in order to obtain efficiency gains. This is true in the field of cultural heritage preservation, and particularly in the case of public historical archives (PHAs), where the application of media and digitisation technologies has manifold implications ranging from the preservation, to production and usage of cultural goods.

DT can improve preservation and deter the decay of fragile items, as well as lower the cost of duplication and transfer, because the replaceability of the original document with its digital copy, usually without any relevant shortcomings for the user. Moreover, DT radically affects utilisation insofar the consumption of cultural services can be done either by visiting an archive, and consulting the documents stored there, or digitally, by browsing the archive website to retrieve digitised documents and records. The impact of DT would reasonably depend on the degree of digitisation of the documents preserved by archives as well as on the quantity and quality of information recorded in the websites. Websites are the form of DT most widely adopted by cultural institutions, such as the PHAs, since it is a digital infrastructure which is necessary for the development of other more advanced technologies and its adoption has tiny costs (Guccio et al., 2016). Websites provide, in some instances, only basic information on the archive (address, opening times,…); however, they may also include detailed information on cultural goods preserved and available for physical utilisation. In this case, websites work as a *complementary* service to the physical utilisation of cultural goods, by reducing the costs of information and research for users. Finally, when access to digitised products is available, digital utilisation can be a *substitute* of physical utilisation. For the abovementioned reasons, websites can have a relevant impact in the management of PHAs and may be critical for their performance. Moreover, their use can be considered an indicator of the ability to innovate (Borowiecki and Navarrete, 2015). The previous issues suggest that the connection between PHAs' websites and efficiency is a complex question that has not been thoroughly studied so far, in spite of the centrality of archives as information suppliers.

In this paper we start filling this lacuna by investigating Italian PHAs. More specifically, we use a panel data including 99 Italian PHAs for the period 2009-2014. In our analysis, we first distinguish PHAs according to the time of adoption of a website, and study their differences in terms of productivity. To analyse the influence of website on efficiency, we apply a two-stage empirical strategy, which involves the estimation of the efficiency frontier by employing non-parametric techniques, namely Data Envelopment Analysis (DEA), and the use of Mann-Whitney and Kolmogorov-Smirnov tests, as well as second stage regression (Banker and Natarajan, 2008; Simar and Wilson, 2007). Finally, we apply Window Data Envelopment Analysis (WDEA) to study the efficiency trend in the observed period.

This paper contributes to the existing literature on cultural heritage by being the first study, to the best of our knowledge, assessing the impact of DT on the efficiency of Italian PHAs.

This paper is organised as follows. Section 2 provides a review of the relevant literature as well as an overview on Italian PHAs and the spread of DT. Section 3 describes the methodological framework. Results are shown in Section 4. Some comments conclude the paper.

2. Background and literature review

2.1 Literature review

A growing number of studies have analysed the impact of DT on cultural policy (see Flew and Swift 2013; Towse and Handke 2013; Handke et al., 2013). This is generally acknowledged to be multidimensional acting on both supply and demand of cultural goods (Navarrete, 2013a). Recent works have focused on museums (Navarrete, 2013b; Paolini et al., 2013), libraries (Salaun, 2013), and PHAs (Guccio et al., 2016). The website usage is of considerable interest for its large diffusion and for its relevance as a basic digital tool, able to foster the diffusion of more complex technologies (Guccio et al. 2016). In fact, websites are used for a wide range of services, from the delivery of information to the direct provision of services.

However, although internet represents the most relevant digital infrastructure, scholars have so far neglected to investigate the effect of its usage on the efficiency of cultural organizations.

Similarly, the interest in assessing the performance of cultural organizations is relatively recent, although it has grown rapidly in the last decades. Efficiency frontier estimation has been increasingly widespread in the cultural sector (Pignataro, 2002, 2011; Mairesse and Vanden Eeckaut, 2002; Bishop and Brand, 2003; Basso and Funari, 2004; Del Barrio et al., 2009; Finocchiaro Castro and Rizzo, 2009; Finocchiaro Castro et al. 2011; Zieba, 2011; Fernandez-Blanco et al., 2013; Del Barrio and Herrero, 2013) to assess the efficiency of museums and other cultural institutions, as well as of libraries (Chen, 1997; Vitaliano, 1998; Hammond, 2002; Kao and Lin, 2004; Reichmann, 2004; Chen et al., 2005; Simon et al., 2011; De Witte and Geys, 2011, 2013).

With the only exception of Guccio et al. (2015), PHAs' efficiency has not been studied so far. In particular, Guccio et al. (2015) models a multistage production process to disentangle PHAs' activities and studies the efficiency in the preservation and enhancement activities. Although our work has several aspects in common with the latter, a number of differences exist. We study here the impact of DT on PHAs' efficiency in enhancement activity, and control for preservation as websites are a DT affecting the enhancement of cultural heritage. We, furthermore, use a larger dataset and apply estimation techniques that allow for analysing the dynamic of efficiency consistently.

2.2 Italian PHAs, collections and websites

Italian State Archives are 101 peripheral entities of the Italian Ministry for Heritage, Cultural Activities and Tourism (*Ministero dei Beni e delle Attività Culturali e del Turismo*, MiBACT), mainly located in provincial capital towns, which are devoted to the archival function.

Their functions involve the conservation, preservation and enhancement of a huge amount of administrative and culturally relevant documents. Their collections include a wide range of items, such as manuscripts, parchments, sound recording,

Table 1. Descriptive statistics of Italian PHAs – regional averages - year 2012

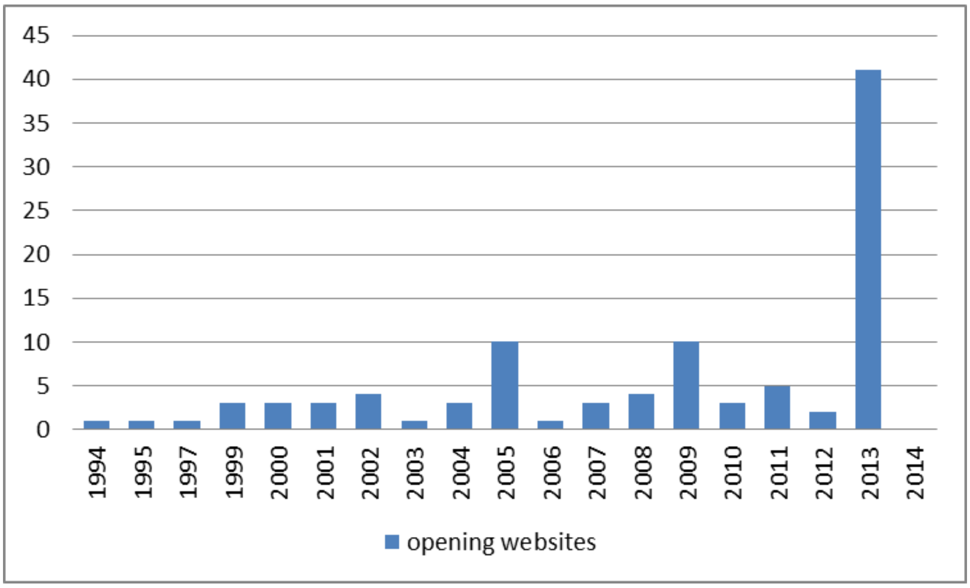
Regions and area	Number of PHAs	Number of sections	Total surface area (square meters)	Shelfs (linear meters)	Personnel (number)	Current expenditure (Euro)	Number of visitors	Number of requests	Number of document inspected	Number of manuscripts and documents
Piemonte	8	1	68,474	160,694	136	2,424,220.98	39,056	28,856	47,670	1,164,326
Lombardia	9	-	49,686	137,558	130	1,585,172.55	27,913	8,101	73,300	1,190,895
Trentino-Alto Adige	2	-	3,773	14,908	14	167,696.64	1,687	923	3,729	112,718
Veneto	7	1	58,057	139,226	182	1,343,835.71	31,029	9,944	67,566	1,061,901
Friuli-Venezia Giulia	4	-	12,049	44,012	45	393,921.81	7,085	3,787	36,540	320,461
Liguria	4	2	11,051	38,355	68	610,167.32	8,471	2,379	42,751	422,072
Emilia Romagna	8	3	47,843	167,926	149	1,026,853.55	19,971	5,472	64,727	1,104,782
North	***42***	***7***	***250,933***	***702,679***	***724***	***7,551,868.56***	***135,212***	***59,462***	***336,283***	***5,377,155***
Toscana	10	2	60,234	164,234	211	1,522,441.15	30,882	15,913	72,366	1,378,069
Umbria	2	5	14,340	38,484	114	288,001.40	10,000	2,394	17,518	294,262
Marche	5	4	20,258	64,616	114	377,396.00	10,769	3,005	67,011	539,400
Lazio	5	1	29,418	106,577	167	1,428,541.29	16,431	4,806	49,480	1,285,029
Centre	***22***	***12***	***124,250***	***373,911***	***606***	***3,616,379.84***	***68,082***	***26,118***	***206,375***	***3,496,760***
Abruzzo	4	3	18,482	46,801	112	485,634.37	7,870	3,130	37,541	414,000
Molise	2	-	5,120	11,825	72	193,010.71	1,978	819	37,725	132,503
Campania	5	-	46,310	99,017	220	1,182,315.96	12,589	6,964	38,055	787,145
Puglia	5	3	23,578	83,730	237	1,260,094.40	13,281	7,682	86,911	738,927
Basilicata	2	-	4,727	19,023	43	251,303.81	3,225	997	7,584	188,826
Calabria	4	4	16,939	36,558	205	496,253.30	8,103	4,303	27,238	306,972
Sicilia	9	5	34,008	116,638	259	1,886,150.86	13,295	4,523	78,781	1,006,934
Sardegna	4	-	7,237	16,117	68	646,893.47	5,928	1,759	17,987	340,512
South	***35***	***15***	***156,401***	***429,709***	***1,216***	***6,401,657***	***66,269***	***30,177***	***331,822***	***3,915,819***
All sample	**99**	**34**	**531,584**	**1,506,299**	**2,546**	**17,569,905.28**	**269,563**	**115,757**	**874,480**	**12,789,734**

films, drawings, etc. Table 1 displays the descriptive statistics of items preserved by Italian PHAs, grouped by regions.[1]

The enhancement function results mainly in for-studying and not-for-studying research by private users, and also in visiting exhibitions or the buildings, as several archives are located in valuable buildings from historic and architectonic perspectives.

Currently, all PHAs have a website and a large majority is hosted in the MiBACT domain *beniculturali.it*. Although websites have low costs of opening and maintenance, and their diffusion has been widespread in the last years, the timing of adoption by Italian PHAs has been quite dissimilar. Figure 1 shows that the first archive website was established in 1994 and few other forerunners followed in the succeeding years. Three peaks occurred in 2005, 2009 and, finally in 2013. The latter involved the residual 40% of PHAs and was directly enforced by the MiBACT.

Figure 1. Italian PHAs opening websites by year.



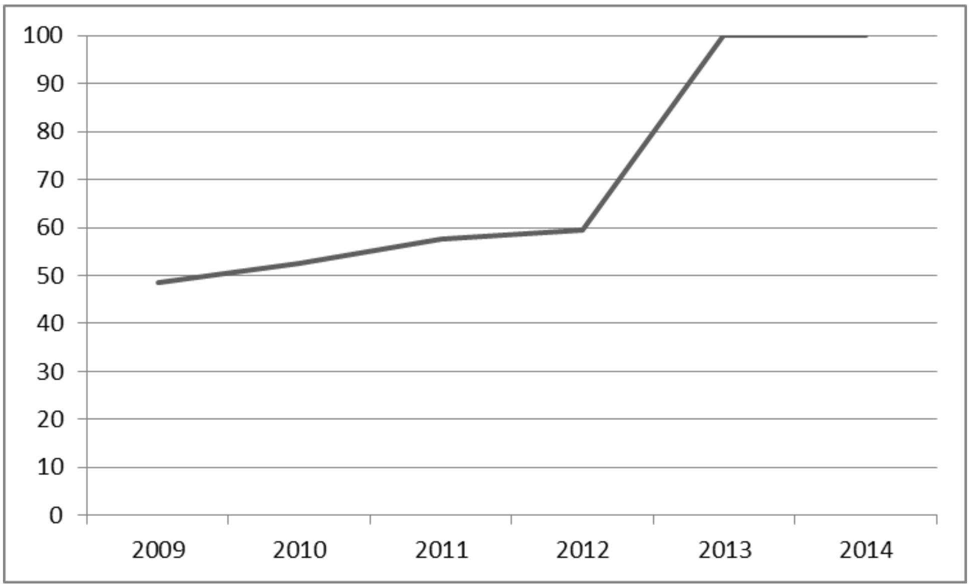
Source: our elaboration.

Several Italian PHAs introduced more advanced DT, but the implementation process is still undergoing. The digitisation of collections is still incomplete,

[1] We exclude the National Central Archive in Rome for its specificity and the archive of Ferrara for its data incompleteness.

although it has been fostered starting by 2008, and online access to digital items is available for very few PHAs (Guccio et al. 2016). While the digital infrastructure (websites) has been fully implemented in the last few years, the potential improvement to digital consumption are still negligible. We therefore focus on website adoption and explore the connection between the efficiency of PHAs and the diffusion of website usage.[2] We preliminarily display productivity indexes (the number of visitors to a PHAs per unit of personnel, and the number of enquiries per unit of personnel) discriminating PHAs according to their propensity to DT. To do so, we need to define a cut-off point so as to split PHAs between those that had a website before that date and the rest. We choose 2009 as this is the first website opening peak within our sample period.[3]

Figure 2. Percentage of Italian PHAs having websites. 2009-2014



Source: our elaboration.

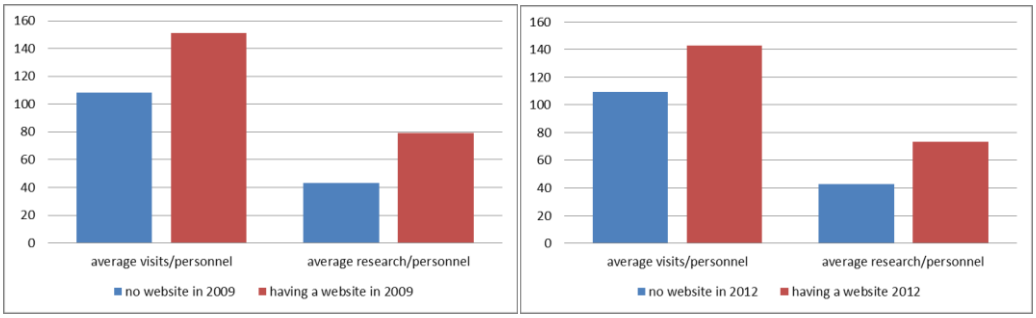
Moreover, as shown in Figure 2, the last available peak occurred in 2013, and so we use 2012 as a cut-off to distinguish PHAs that were very resistant to innovation

[2] See Guccio et al. 2016 for a more detailed description of MiBACT's projects involving DT and the use of internet.

[3] In Section 4 we also consider 2008 and 2010 to show that our cut-off choice does not affect result and to take into account the fact that we do not observe true opening times, which lie at some point between two consecutive years.

and started using website only because of MiBACT's pressure. Figure 3 displays the productivity indexes for the groups of PHAs distinguished as mentioned above.

Figure 3. Productivity indexes for groups of PHAs.



Source: our elaboration on data provided by MIBACT Statistical office.

Irrespective of the cut-off, more innovative PHAs show on average higher productivity in terms of visits and researches per unit of personnel. Notice the remarkable difference between them, especially in the average number of researches per unit of personnel.

To analyse efficiency and website usage, however, a different and more advanced technique is necessary as productivity indexes have some drawbacks. In fact, a productivity index is a ratio of a single output to a single input whereas economic efficiency of a producer involves a comparison between observed and optimal values of outputs and inputs. Moreover, indexes do not allow for taking account of production functions involving multiple inputs and outputs, scale effects on performance and comparisons of different units of analysis.

Frontier methods, such as DEA, can therefore be more appropriate techniques than indexes to measure and assess the performance of a group of comparable organizations.

3. Methodological framework

3.1 DEA and Window DEA

DEA Window Analysis was introduced by Charnes and Cooper (1985), and it extends DEA (Charnes et al., 1978). Among the available frontier estimation techniques, DEA is acknowledged for its flexibility, as it can be applied to multiinput/multi-output settings, and does not require explicit specification of the functional form. The DEA approach measures efficiency through the estimation of a frontier envelopment surface for all DMUs (i.e. Decision Making Unit) by using linear programming techniques. It constructs envelopment unitary isoquants corresponding to comparable DMUs and identifies as productive benchmarks those DMUs that exhibit the lowest technical coefficients, that is, the lowest amount of inputs to produce one unit of output.[4]

Considering *N* DMUs (*i=1,…., N*) to be evaluated, DEA calculates an efficiency score θ_i for each DMU by solving the following program, for *i=1,…., N*, assuming constant returns to scale (CRS):

$$Max_{\lambda,\theta_i}\,\theta \qquad [1]$$

$$s.t.\ x_i \geq X\lambda$$

$$\theta_i y_i \leq Y\lambda$$

$$\lambda \geq 0$$

where x_i and y_i are, respectively, the input and output of i-th DMU; *X* is the matrix of inputs and *Y* is the matrix of outputs of the sample; λ is a $n\times 1$ vector of weights which allows to obtain a convex combination between inputs and outputs. Banker et al. (1984) modified the model (1) to account for variable returns to scale (VRS) by adding the convexity constraint: $e\lambda=1$, where *e* is a row vector with all elements unity that allows to distinguish between Technical Efficiency and Scale Efficiency. Solving [1], DMUs with an efficiency score equal to one are located on the frontier and therefore their outputs cannot be further expanded without a corresponding increase in inputs.

Simar and Wilson (1998, 2000) developed a bootstrapping methodology to determine the statistical properties of DEA estimators and account for DEA's traditional limitations, which do not allow for any statistical inference and measurement error. The bootstrap procedure approximates the sampling distributions of efficiency scores by simulating their Data Generating Process

[4] For further details see Fried et al. (2008).

(Simar and Wilson 2008). In fact, Simar and Wilson (2000) provide a flexible procedure which automatically corrects for bias without the explicit use of a noisy bias estimator.[5] We adopt this procedure also because it does not assume homogeneity on the distribution of efficiency, which may be too restrictive for our analysis and invalidate the inference on our efficiency estimates.[6]

As a robustness check and to analyse the efficiency trend, we also use DEA Window analysis to study efficiency over time. DEA Window analysis applies the moving averages and allows for dynamic effects in panel data. More specifically, this approach considers each DMU in a different period as if it is a different unit. A DMU's performance in a specific period is compared with its performance in other periods in addition to the performance of the other DMUs.

More formally, following Asmild et al. (2004), let consider *N* DMUs (*i=1,…., N*) that are observed in T (*t=1,…., T*) periods and use *s* inputs to produce *r* outputs. DMU_i^t represents an observation *n* in period *t* with input vector $\boldsymbol{x}_i^t = (x_i^{1t}, \dots x_i^{st})'$ and output vector $\boldsymbol{y}_i^t = (y_i^{1t}, \dots y_i^{rt})'$. If the window starts at time *k* $(1 \leq k \leq T)$ with width denoted by *w* $(1 \leq w \leq T - k)$, then the matrices of inputs and outputs are denoted respectively as follows:

$$\boldsymbol{X}_{kw} = [x_1^k, x_1^{k+1}, \dots, x_1^{k+w};\ x_2^k, x_2^{k+1}, \dots, x_2^{k+w};\ x_N^k, x_N^{k+1}, \dots, x_N^{k+w}] \qquad [2]$$

$$\boldsymbol{Y}_{kw} = [y_1^k, y_1^{k+1}, \dots, y_1^{k+w};\ y_2^k, y_2^{k+1}, \dots, y_2^{k+w};\ y_N^k, y_N^{k+1}, \dots, y_N^{k+w}] \qquad [3]$$

Then, inputs and outputs of DMU_i^t are substituted into equation [1].

The choice of the length of the window is an important issue in DEA Window analysis. In this study we use 99 Italian PHAs *(N=99)* for the time period 2009–2014 *(T=6)*. As Asmild et al. (2004) highlights, it is assumed that there are no technical changes within windows; therefore, a narrow window width must be used. In the literature following this approach, usually, a window length of *k=3* is employed.

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[5] See Simar and Wilson (2008) for the technical detail of the bootstrap procedures.
[6] See Section 4 for a detailed discussion on this point.

3.2 Assessing the connection between website usage and efficiency

We test equality of distribution in the efficiency scores of the group of PHAs having the website against those that have not websites through the Mann-Whitney and Kolmogorov-Smirnov tests, and according to different cut-offs. As a robustness check, we also employ a second stage analysis and regress efficiency scores θ_i on a vector of variables z_i. The general model is the following:

$$\theta_i = f(z_i) + \varepsilon_i \qquad [3]$$

where $\varepsilon_{i,t}$ is the error term.

Simar and Wilson (2007) state that common estimators such as Tobit and OLS are biased because of the violation of independence between z_i and ε_i. Although there is no general consensus on the method to be used in order to account for such a bias (Simar and Wilson, 2007; 2011; Banker and Natarajan, 2008; McDonald, 2009), the two-step bias-corrected semi-parametric estimator proposed by Simar and Wilson (2007) ensures a feasible, consistent inference on the parameters for estimation in the second stage of the regression. However, Banker and Natarajan (2008) generate statistically consistent estimators for the two-stage procedure, which involve nonparametric estimation of productivity in the first stage followed by OLS regression. Notably, Banker and Natarajan argued that their statistical model requires less restrictive assumptions than the Simar and Wilson model (2007). Hence, we employ the Banker and Natarajan procedure (2008) as well as that by Simar and Wilson (2007) to provide robustness to our results.

3.3 Inputs and outputs selection

The identification of the production process and the choice of appropriate set of inputs and outputs has proven to be the most challenging aspect in analysing cultural organizations and, among them, PHAs.

Regarding museums, for example, Mairesse and Vanden Eeckaut (2002), Basso and Funari (2004), and Del Barrio and Herrero (2013), use dissimilar variables as inputs (such as: employees, occasionally divided into scientific and technical personnel, operational budget, security services, size of exhibition rooms), and outputs (preservation, research and communication, opening hours, visitors, exhibitions, social impact). Also studies on libraries' efficiency (Chen, 1997; Hammond, 2002) offer a wide range of choices for inputs and outputs. Among the former inputs, we can find staff, collection, library space, opening hours, infrastructure. Simon et al. (2011) and De Witte and Geys (2011) use a two-stage model. The former considers infrastructure and library resources as intermediate output for the final consumption of library services, while the latter uses the collection and opening hours as intermediate output. Guccio et al. (2015) is the only work assessing PHAs' efficiency, to the best of our knowledge. It studies the performance of Italian PHAs in 2011-2012 and employ several models including two-stage production processes. Inputs include a set of 4 variables (total surface area, shelves' dimension, number of personnel and current expenditures) to perform the preservation function, which is identified by three physical measures of preserved heritage (number of manuscripts and documents, antiquaries, and other collections). Final outputs include the number of visitors, processed requests for both scientific and non-scientific purposes, and inspected documents. We follow Guccio et al. (2015) in the selection of relevant variables, noticing however that, unlike that study, we do not distinguish PHAs' preservation and enhancement efficiency. Moreover, we include not only the physical measure of preserved heritage but also its monetary value, as control for the preservation function in the second stage.

We consider the production process for PHAs involving the use of multiple inputs to produce several outputs. Inputs include measures of the available collections, personnel as well as buildings, rooms, and deposits. More in particular, we consider a set of N inputs: the total surface area (SURFACE) in square meters, and the total shelf's dimension (SHELF) in linear meters, as proxies of the infrastructural endowment; the number of personnel (PERS) and current PHA expenditure (EXP), excluding labour costs, as current inputs.

Outputs include the number of visitors (VISITORS), the total number of requests processed by PHA for both scientific and non-scientific purposes (RESEARCH), and the total number of documents inspected (D_RESEARCH). We only include a set of inputs and outputs focusing on the enhancement function. To control for the latter functions we include measures of the heritage managed by the PHAs in the second stage, namely, the number of items collected (ITEMS) and the asset value (ASSET_VALUE) of PHAs' collection.

3.3 Data

The above inputs and outputs are drawn from the *Sistema Statistico Nazionale* (*SISTAN*) and include, for each PHA, information on physical endowment, staff, items preserved, physical utilisation, etc. Information on the year since PHAs have a website (YEAR_SINCE) are acquired from a web repository (*Internet Archive – Wayback Machine*) and by browsing archives' websites. Data on the asset value (reported in hundred thousand euros at current prices) of PHAs' preserved collections derive from the Italian Ministry of Economy and Finance (*Ministero dell'Economia e delle Finanze*, MEF). Finally, data on websites visits (W_VISITS, reported in ten thousands) originate from PHAs' website statistics. Data were analysed for reporting errors, outliers and missing values. The final sample consists of a sample of cross-sectional and time series observation for 99 Italian PHAs for 6 years (2009-2014), thus resulting in 594 observations.[7]

Table 2. Descriptive statistics

Variables	Obs.	Mean	St. Dev.	Min	Max
		Frontier estimation			
Inputs					
SURFACE	594	5400.96	6135.81	340.00	36141.00
SHELF	594	15,228.78	16,604.78	1,992.00	90,000.00
PERS	594	25.97	20.00	3.00	124.00
EXP	594	205,939.66	259,817.82	15,465.00	205,939.66
Outputs					
VISIT	594	2,807.63	3,384.99	58.00	30,678.00
RESEARCH	594	1,206.70	2,031.23	124.00	24,684.00
D_RESEARCH	594	9,095.02	9,447.66	269.00	71,016.00
		Second Stage			
Variables on websites					

[7] YEAR_SINCE defines a subsample since some PHAs did not have a website even in the sample, as reported in Figure 2. W_VISIT defines a subsample because observations required additional cleaning procedures and are also characterized by several missing data.

t2008	594	0.38	0.49	0.00	1.00
t2009	594	0.48	0.50	0.00	1.00
t2010	594	0.52	0.50	0.00	1.00
t2012	594	0.59	0.49	0.00	1.00
YEAR_SINCE	411	5.28	4.65	0.00	20.00
W_VISIT	249	10,526.96	16,990.37	0	12,644.00
Control Variables					
ASSET_VALUE	594	12,012.11	24,117.63	0.71	200,231.00
ITEMS	594	22.60	40.42	1.10	346.04
YEAR2009	594	0.17	0.37	0.00	1.00
YEAR2010	594	0.17	0.37	0.00	1.00
YEAR2011	594	0.17	0.37	0.00	1.00
YEAR2012	594	0.17	0.37	0.00	1.00
YEAR2013	594	0.17	0.37	0.00	1.00
YEAR2014	594	0.17	0.37	0.00	1.00
North	594	0.22	0.42	0.00	1.00
Centre	594	0.42	0.49	0.00	1.00
South	594	0.35	0.48	0.00	1.00

Source: our elaboration.

In addition to inputs, outputs and heritage controls, we also use a set of 6 variables on website usage, time fixed effect dummies and geographical area dummies. A detailed description of such variables is given in Section 4, while descriptive statistics for all variables are shown in Table 2.[8]

4. Results and discussion

4.1 Frontier estimation and websites.

In what follows, we use an output-oriented approach and assume VRS as a reference technology.[9]

To check for the robustness of the DEA findings with respect to the sampling variation, we also employ the Simar and Wilson, (2000) bootstrap procedure with 2,000 bootstrap draws. However, Simar and Wilson (2008) point out that the bias correction obtained with bootstrap procedures introduces additional "noise" in the efficiency estimates. They show that the bias correction provides valid inference only if the ratio of the estimated bias to the variance satisfies some conditions.[10] As

[8] We thank the General Direction for Italian Archives for its support in the collection of data.

[9] The Banker (1996) test shows that in our sample we can reject the null hypothesis of CRS at 5 percent level of significance. Results are available upon request.

[10] For further details see Simar and Wilson (2008).

a caution rule, they suggest that the bias correction should not be used if correction is larger than four times the variance of efficiency scores obtained from all bootstrapped pseudo-samples, as in our estimation (Table 3). [11]

Table 3 shows the distribution of DEA efficiency scores by group of archives, defined by the cut-offs described in Section 2: for instance, T2009 classifies PHAs having a website in 2009. We also add T2008 and T2010, to show that the cut-off choice does not affect the results, and T2012. In general, estimation outcomes show that PHAs have, on average, a low level of efficiency. Interestingly, results show that, independently from the cut-off choice, the groups of PHAs having already a website have also a higher level of efficiency if compared with the whole sample. This is consistent with preliminary results on productivity indexes. However, the average score for the group of website forerunners is decreasing in the cut-off. Table 3 also reports in the last columns the statistics of the bias correction obtained through the bootstrap procedure.

Table 3. Efficiency estimates for different groups of archives under VRS

Groups	**Number of obs.**	**Efficiency scores**		**Bias corrected efficiency scores**		
		Mean	**St. Dev.**	**Mean**	**Average bias correction**	**Average variance in bootstrapped pseudo samples**
All archives	594	0.3842	0.2545	0.3075	-0.0783	0.0062
T2008	*228*	*0.4168*	*0.2518*	*0.3362*	*-0.0806*	*0.0052*
T2009	*288*	*0.4132*	*0.2559*	*0.3298*	*-0.0834*	*0.0058*
T2010	*306*	*0.4039*	*0.2530*	*0.3232*	*-0.0807*	*0.0056*
T2012	*348*	*0.3897*	*0.2451*	*0.3127*	*-0.0770*	*0.0051*

Source: our elaboration on data provided by MIBACT Statistical office.

However, to identify the most efficient groups of archives and, therefore, the best practices, we assess the equality of the distributions of the efficiency scores for the different groups of archives according to different timing on use of web (i.e. different cut-offs). To test for significant differences in the DEA efficiency

[11] It also makes Banker and Natarajan (2008) two-stage approach more appropriate than Simar and Wilson (2007). However, in the second-stage estimate Tables we use both procedures as a robustness check.

estimates of the archives' groups, we perform two tests, namely the Mann-Whitney and Kolmogorov-Smirnov tests. Results are shown in Table 4.

Table 4. Testing for differences on the average efficiency scores of the different groups of archives, defined by the cut-offs.

Efficiency estimates in subsamples	**No website *vs.* having website**	
	MW	*KS*
T2008	-3.125 (0.0018)	0.1651 (0.0009)
T2009	-3.203 (0.0014)	0.1509 (0.0019)
T2010	-2.517 (0.0088)	0.1399 (0.0058)
T2012	-1.512 (0.1306)	0.0982 (0.0916)

Note: Mann–Whitney (MW) test; Kolmogorov–Smirnov (KS) two-sample test. *p-values* in parentheses. *Source: our elaboration on data provided by MIBACT Statistical office.*

Differences in mean efficiency are in general significant. In fact, the null hypothesis that the two samples are drawn from the same distributions can be rejected at any conventional level of significance both for Mann-Whitney and Kolmogorov-Smirnov tests for groups defined by T2008, T2009, and T2010. T2012 does not provide evidence of difference between groups.

4.2 Second stage approach.

Previous Section shows that, on average, the PHAs that employ websites are more efficient in the fruition function.

However, to attribute these differences in the performance significantly to the role of website, we must control for other environmental factors that may affect PHAs' performance. In particular, we add several controls, including time and geographical area[12] fixed effects, and two measures of heritage collected by PHAs, namely the number of items preserved (ITEMS) and their economic value

[12] We consider three geographical areas: North (Emilia Romagna, Friuli, Liguria, Lombardia, Piemonte, Trentino, Veneto), Centre (Lazio, Marche, Toscana, Umbria), South (Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, Sardegna, Sicilia)

(ASSET_VALUE). These two variables provide a measure of collections from two different perspectives and are not strongly correlated so we use them alternatively and jointly in the regressions. Therefore, we follow the two-stage approach suggested by Coelli et al. (1998) to regress DEA efficiency estimates against a set of covariates. The two-stage analysis is usually implemented after conducting traditional DEA analyses. However, different estimators have been proposed (Simar and Wilson, 2011). Due to previous findings on potential noise in bootstrap bias correction, here we apply parametric estimators (Banker and Natarajan, 2008).[13]

[13] We also employ semi-parametric estimates (Simar and Wilson, 2007). Results are available upon request.

Table 5. Robust OLS (Banker and Natarajan, 2008).

VARIABLES	DEA_VRS efficiency scores											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
INTERCEPT	0.364***	0.350***	0.348***	0.334***	0.357***	0.343***	0.344***	0.331***	0.363***	0.343***	0.350***	0.337***
	(0.013)	(0.025)	(0.024)	(0.032)	(0.014)	(0.026)	(0.025)	(0.032)	(0.015)	(0.026)	(0.026)	(0.033)
T2008	0.053**	0.053**	0.059***	0.059***								
	(0.021)	(0.021)	(0.021)	(0.021)								
T2009					0.056***	0.056***	0.061***	0.061***				
					(0.021)	(0.021)	(0.021)	(0.021)				
T2010									0.041*	0.041*	0.041*	0.046**
									(0.021)	(0.021)	(0.021)	(0.021)
YEAR2009		-0.004		-0.004		-0.004		-0.004		-0.004	-0.004	-0.004
		(0.035)		(0.035)		(0.035)		(0.035)		(0.035)	(0.035)	(0.035)
YEAR2011		0.027		0.027		0.027		0.027		0.027	0.027	0.027
		(0.034)		(0.034)		(0.034)		(0.034)		(0.034)	(0.035)	(0.035)
YEAR2012		0.025		0.025		0.025		0.025		0.025	0.025	0.025
		(0.036)		(0.036)		(0.036)		(0.036)		(0.036)	(0.036)	(0.036)
YEAR2013		0.018		0.018		0.018		0.018		0.018	0.018	0.018
		(0.036)		(0.035)		(0.036)		(0.035)		(0.036)	(0.036)	(0.036)
YEAR2014		0.016		0.016		0.016		0.016		0.016	0.016	0.016
		(0.035)		(0.035)		(0.035)		(0.035)		(0.035)	(0.035)	(0.035)
NORTH			0.044	0.044			0.040	0.040			0.040	0.040
			(0.028)	(0.028)			(0.028)	(0.028)			(0.028)	(0.028)
CENTRE			-0.015	-0.015			-0.019	-0.019			-0.019	-0.019
			(0.028)	(0.029)			(0.029)	(0.029)			(0.029)	(0.029)
Observations	594	594	594	594	594	594	594	594	594	594	594	594
R-squared	0.010	0.012	0.022	0.024	0.012	0.014	0.023	0.025	0.006	0.014	0.009	0.019

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6. Robust OLS with further controls on heritage magnitude and value

VARIABLES	Robust OLS					
	(1)	(2)	(3)	(4)	(5)	6)
INTERCEPT	0.347***	0.343***	0.336***	0.319***	0.307***	0.289***
	(0.016)	(0.015)	(0.016)	(0.028)	(0.026)	(0.035)
T2009	0.055***	0.044**	0.043**	0.043**	0.048**	0.048**
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
ITEMS_10000	0.000*		0.000	0.000	0.000*	0.000*
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
ASSET_VALUE_100000		0.000***	0.000***	0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
YEAR2009				0.004		0.004
				(0.034)		(0.034)
YEAR2010				0.031		0.031
				(0.035)		(0.035)
YEAR2011				0.029		0.029
				(0.037)		(0.036)
YEAR2012				0.022		0.022
				(0.036)		(0.036)
YEAR2013				0.019		0.019
				(0.035)		(0.035)
NORTH					-0.001	-0.001
					(0.029)	(0.029)
CENTRE					0.059**	0.059**
					(0.028)	(0.028)
Observations	594	594	594	594	594	594

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7. Robust OLS for T2012

VARIABLES	Robust OLS			
	(1)	(2)	(3)	(4)
INTERCEPT	0.376***	0.363***	0.365***	0.352***
	(0.017)	(0.028)	(0.028)	(0.035)
T2012	0.013	0.013	0.018	0.018
	(0.022)	(0.022)	(0.021)	(0.021)
YEAR2009		-0.004		-0.004
		(0.035)		(0.035)
YEAR2010		0.027		0.027
		(0.035)		(0.035)
YEAR2011		0.025		0.025
		(0.036)		(0.036)
YEAR2012		0.018		0.018
		(0.036)		(0.036)
YEAR2013		0.016		0.016
		(0.035)		(0.035)
NORTH			0.036	0.036
			(0.028)	(0.028)
CENTRE			-0.020	-0.020
			(0.029)	(0.029)
Observations	594	594	594	594

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Results are shown in Table 5 and 6 for T2008, T2009, T2010, and Table 7 for T2012. Results confirm previous findings, showing that being in the group of those PHAs having a website before the cut-off date, is associated to a higher efficiency level. In fact, the coefficient of the cut-off dummies is positive and significant, though both are slightly lower for T2009 and T2010 and are not significant for

T2012. The latter points suggest that the improvement associated to the use of internet website increases with the number of years in which the website is in operation. The control variables representing heritage are significant, with positive sign but with an extremely small coefficient.

4.3 Other issues related to website

In line with the abovementioned lower coefficient associated to different cut-offs, we investigate whether the actual usage and seniority of website are relevant in explaining the efficiency of PHAs. We, therefore, apply the second stage approach and use as covariates the number of years starting from when the website has become operative (YEARS_SINCE) and the number of visits to the website (W_VISIT). We show results in Table 8. The effect of the above variables is slightly positive but does not provide evidence against the previously found complementary effect of website. In general, seniority is positively associated to efficiency, suggesting that the effect is increasing in time. Moreover, a larger number of visits, which approximate the demand for website services, positively influence efficiency although the effect is actually small. Such effect disappears almost completely when controlling for PHAs' collection.

4.3 Dynamics of PHAs efficiency using DEA Window.

In order to evaluate the short and long run effect of the website on the performance of archives, we use a DEA Window analysis that enables us to measure efficiency in cross-sectional and time varying data and to detect efficiency trends over time (Asmild et al., 2004). DEA window analysis is employed to assess the trend of technical efficiency over the analysis period. Our approach enables us to provide a simultaneous examination of trends of efficiency over a specified period of time and of the stability and other properties of the efficiency evaluations *across*, as well as *within*, the specified windows. Furthermore, the use of window analysis increases the number of reference points in the analysis and avoids robustness related problems.

Table 8. Robust OLS (subsample of archives with site)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
INTERCEPT	0.366***	0.378***	0.370***	0.389***	0.363***	0.388***	0.347***	0.365***	0.309***	0.365***	0.315***	0.388***
	(0.019)	(0.020)	(0.036)	(0.057)	(0.043)	(0.063)	(0.042)	(0.063)	(0.043)	(0.063)	(0.044)	(0.063)
YEARS_SINCE	0.005*		0.005**		0.005**		0.004		0.003		0.004	
	(0.003)		(0.003)		(0.003)		(0.003)		(0.002)		(0.002)	
W_VISITS		0.000**		0.000**		0.000**		0.000		0.000		0.000**
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
ITEMS							0.001*	0.003***	0.001	0.003***		
							(0.001)	(0.001)	(0.000)	(0.001)		
ASSET_VALUE									0.000***	-0.000	0.000***	0.000
									(0.000)	(0.000)	(0.000)	(0.000)
YEAR2009			0.005	-	0.006	-	0.004	-	0.003	-	0.004	-
			(0.051)	-	(0.052)	-	(0.050)	-	(0.049)	-	(0.050)	-
YEAR2011			0.009	0.008	0.009	0.008	0.010	0.007	0.012	0.007	0.012	0.008
			(0.047)	(0.077)	(0.047)	(0.078)	(0.046)	(0.076)	(0.045)	(0.076)	(0.045)	(0.078)
YEAR2012			-0.021	-0.011	-0.022	-0.012	-0.019	-0.007	-0.016	-0.007	-0.017	-0.012
			(0.047)	(0.075)	(0.047)	(0.075)	(0.046)	(0.074)	(0.045)	(0.074)	(0.045)	(0.076)
YEAR2013			-0.003	-0.009	-0.004	-0.009	-0.005	-0.008	-0.000	-0.008	0.001	-0.009
			(0.043)	(0.064)	(0.043)	(0.065)	(0.042)	(0.063)	(0.041)	(0.064)	(0.042)	(0.065)
YEAR2014			-0.011	-0.023	-0.012	-0.023	-0.012	-0.018	-0.006	-0.018	-0.006	-0.023
			(0.042)	(0.064)	(0.042)	(0.064)	(0.042)	(0.063)	(0.041)	(0.063)	(0.041)	(0.064)
NORTH					0.017	0.008	0.018	-0.008	0.047	-0.008	0.050	0.008
					(0.033)	(0.040)	(0.031)	(0.040)	(0.033)	(0.040)	(0.034)	(0.040)
CENTRE					-0.004	-0.018	-0.006	-0.041	0.024	-0.039	0.029	-0.018
					(0.034)	(0.049)	(0.033)	(0.047)	(0.034)	(0.049)	(0.034)	(0.051)
Observations	411	249	411	249	411	249	411	249	411	249	411	249
R-squared	0.008	0.019	0.010	0.021	0.011	0.022	0.031	0.051	0.066	0.051	0.057	0.022

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

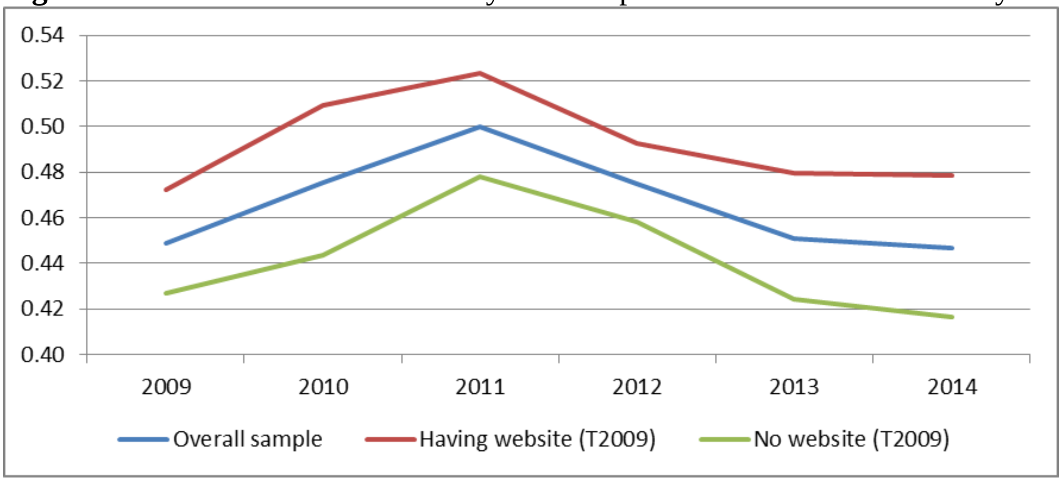
We choose a 3-year window since 3 years is generally appropriate for common frontier and moving average analogue (Asmild et al., 2004).[14] Therefore, in our sample, the mean efficiency scores of each DMU can be calculated for 6 years and for 4 windows. The efficiency trends and levels of each DMU over the period 2009-2014 (i.e. across 6 years) are shown in Table 9 and in Figure 4.[15]

Table 9. Technical efficiency of archives by use of website over the period 2009 to 2014 when it was estimated across 6 years

		T2008		T2009		T2010	
Year	Overall	No website	Having website	No website	Having website	No website	Having website
2009	0.45	0.42	0.49	0.43	0.47	0.44	0.46
2010	0.48	0.45	0.52	0.44	0.51	0.45	0.50
2011	0.50	0.49	0.52	0.48	0.52	0.49	0.51
2012	0.47	0.46	0.49	0.46	0.49	0.47	0.48
2013	0.45	0.43	0.48	0.42	0.48	0.43	0.47
2014	0.45	0.42	0.49	0.42	0.48	0.42	0.47
Mean	0.47	0.45	0.50	0.44	0.49	0.45	0.48

Source: our computation.

Figure 4. Trend of technical efficiency over the period 2009 to 2014 across 6 years



In general, estimation outcomes confirm that PHAs have, on average, a low level of efficiency. Average efficiency increased between 2009 and 2011 and then

[14] We have 4 windows over the period 2009 to 2014 because, when a new period is introduced into the window, the earliest year is dropped. Thus, the first window includes the first 3 years of the period: 2009, 2010 and 2011. In the second window, the year 2009 is excluded and the year 2012 is included and so on. Since DEA Window Analysis treats a DMU independently across the entire period, 4 three-year windows considerably increase the number of observations of the sample.
[15] Trends and levels across 4 windows are available upon request.

decreased. The group of PHAs having website (no matter the cut-off) systematically show higher average efficiency, confirming previous results. However, trends of the groups of PHAs are almost identical, suggesting that websites did not limit the decreasing dynamics of efficiency.

5. Concluding remarks

This paper assesses Italian PHAs' performance in the fruition function, in 2009-2014 and explores the link between efficiency and website usage. Using non-parametric frontier estimation techniques, distribution tests and second stage regression, we obtain several results. First, Italian PHAs are in general characterised by low and stagnant levels of efficiency. This implies that the policies to enhance the performance of PHAs are not effective. To this purpose, a suggestion would be to investigate governance and the related set of incentives. Second, website adoption in recent years seem to have helped forerunners to be more efficient. We interpret this result as an evidence of complementarity between website and the *in situ* examination of documents, at least in terms of better information and accessibility. In fact, although websites have been adopted by all the PHAs, more advanced DT is still unavailable for the large majority of archives. As a consequence, websites mainly provide relevant information on PHAs' services and collections, which reduce users' information costs and uncertainty (regarding the presence of specific documents). Such effect is slightly increasing in the seniority and usage (online visits) of the websites, the latter being influenced also by the website content. Conversely, the limited digitisation of preserved material as well as the absence of online access to digital items for the large majority of PHAs restrain the potential of DT as a substitute of traditional *in loco* fruition.

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