Does high speed railway impact airport efficiency? The Italian case.

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Abstract

This paper investigates the impact of the development during the period 2003-2014 of High-Speed Railway (HSR) infrastru0cture on the efficiency of the overall airport system in Italy. The Italian case was selected for the peculiar characteristics of its travel infrastructure system. We employ a two stage estimation. Following Simar and Wilson (2007), in the first stage we implement data envelopment analysis (DEA) to obtain airport efficiency scores, which, in the second stage, are regressed with the variables of interest. We find evidence of a positive impact of HSR on airport efficiency, with airports located in the North of Italy and close to HSR performing better, while airports with no HSR are find to be inefficient. To support our argument, we provide robustness checks for the presence of international flights and low cost companies. The results of this study should help policy decisions about future investments to improve the efficiency of regional travel systems.

Keywords: High Speed Railway (HSR); Italian airports; Data Envelopment Analysis (DEA); efficiency; infrastructure.

1. Introduction

At the beginning of the 21st century, Western European airport systems have been characterised by structural changes in their fundamentals. The main processes can be summarised in four points: a) an increasing presence of low cost companies; b) the world economic crisis which affected the volume of goods and passengers being transported; c) the on-going privatization of airports; and d) stronger competition between High-Speed Railway (HSR) and air transport. A substantial body of literature have investigated the effects of the first three points, a summary of this literature is provided below.

This paper focuses on the last point, namely the impact of the expansion of the HSR infrastructure on the airport systems. Existing literature on this subject is available for France, Spain and Japan and investigates HSR as a substitute for air travel (Clewlow et al., 2014), and the impact of travel time and price on market share for specific city pairs (Bhadra, 2003; Bonvino et al., 2009). In this paper we turn our attention to the case of Italy, where major investment in the development of HSR were made in the first decade of the 21st century.

This paper tries to enrich the present literature in two directions. Firstly, it tries to shed light on the links between air and rail transportation in Italy upon which literature is limited, secondly it attempts to provide a methodological contribution to evaluate the impact of HSR on the efficiency of the air transport system by considering a specific national and temporal context. To this aim, we employ a dataset of 31 Italian airports observed during the period 2003-2014.

In line with a global trend, during the period 2003-2014, the Italian air transport system has been characterized by major structural changes and policy interventions (including the privatization of airports) aimed at boosting competition among companies and hubs (Curi et al., 2010). In the context of airports, the parallel emergence of low cost companies and development of HSR are considered by some policy makers and scholars as substitute goods. A number of works has investigated different, interesting dynamics of the Italian airport system and their implications for efficiency.

To address this question, we employ a two stage estimation. Following Simar and Wilson (2007), in the first stage we implement data envelopment analysis (DEA) to obtain airport efficiency scores, which are regressed in the second stage with the variables of interest. In this paper, we adopt important features of the study by Gitto and Mancuso (2012a). In particular, we include the same variables (and additional ones) to analyse the Italian airport system efficiency, and we also regress them with the variables of interest.

The paper is organized as follows: Section 2 provides a survey of the literature on the efficiency of air transport systems in various world regions; Section 3 describes the study methodology; Sections 4 and 5 present the data and variables, and the results. Section 6 concludes by highlighting some policy implications and limitations of the study.

1. Literature survey

Literature on airport efficiency identifies three different performance and productivity analysis methods for airports: Index Number method, Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). For example, within the Index Number method, recently Randrianarisoa et al. (2015) applied Total Factor Productivity as measure of efficiency and show that corruption has negative impacts on airport operating efficiency and that airports under mixed public–private ownership with private majority achieve lower levels of efficiency when located in more corrupt countries. SFA and DEA are surveyed by Liebert and Niemer (2010) in the context of airports. The former involves regression analysis, is simpler to implement, but relies strongly on distributional hypothesis and is used extensively in the presence of one output and multiple inputs. The latter uses a linear programming calculus to optimize airport decisions involving the allocation of multiple inputs and multiple outputs, without imposing a distributional hypothesis and has been widely applied in research on technical efficiency (Emrouznejad et al., 2008) and in evaluating transportation efficiency (Emrouznejad and Cabanda, 2014). For the purpose of this paper we selected the non-parametric approach. The main contributions are reviewed in the next section and presented in Table 1.

1.1. Non parametric frontier analysis

The study of airport efficiency and its determinants has seen several contributions analysing the airport system of different countries, and using the stand-alone DEA, or integrating this with principal component analysis (PCA) (Adler and Berechman, 2001), SFA (Pels et al., 2003), two stage procedure (Barros and Dieke, 2007; Örkcü et al., 2016), fuzzy DEA (Wanke et al., 2016) and network DEA (Liu, 2016).

Among the first works, research analyses performance of British Airports before and after privatisation (Parker, 1999), efficiency and productivity changes of Spanish airports using Malmquist indices (Murillo-Melchor, 1999), US airports (Gillen and Lall, 2001; Sarkis, 2000).

Adler and Berechman (2001) apply DEA and PCA to determine the relative efficiency and quality of airports using airline's airport quality from the perspective of airlines rather than passengers' opinion and find that airlines' evaluation of the airports vary considerably relative to quality factors and airports. Specifically, non-European airports were evaluated by airlines as offering the highest quality.

Pels et al. (2003, 2001) study the European airports and find that a number of these operate under decreasing return to scale. They apply DEA and SFA methodology and show that the two lead to similar results. They find that the average European airport operates under constant returns to scale in producing air transport movements and under increasing returns to scale in producing passenger movements.

Sarkis and Talluri (2004) focus on airport performance measurement and evaluate the operational efficiencies of 44 major US airports across 5 years using multi-criteria non-parametric models. The efficiency scores are treated by a clustering method in identifying benchmarks for improving poorly performing airports.

Barros and Sampaio (2004) analyse the technical and allocative efficiency of Portuguese airports in order to identify the best performers and suggest improvement to the least performing airports. By the decomposition of the Malmquist index, Fung et al. (2008) identify the major source of productivity growth in the Chinese airports between 1995-2004, to be technical progress, rather than an improvement in efficiency.

Barros and Weber (2009) estimate the total factor productivity of UK airports using a Malmquist index. Productivity change is factored into an index of efficiency change and an index of technological change. Technological change is further decomposed into indices that measure bias in the production of outputs, bias in the employment of inputs, and the magnitude of the shift in the production frontier. Airports are ranked according to their productivity change over the period 2000-2005. In the majority of cases, UK airports showed no efficiency improvements during the period analysed.

Gitto and Mancuso examine efficiency issues in relation to the Italian airport industry, using non-parametric methods (Curi et al., 2011; Gitto & Mancuso, 2012a, 2012b, 2015). Gitto and Mancuso (2012a) investigate efficiency in Italian airports based on 28 airports analysed over the period 2000-2006. They find that the Italian airport industry experienced significant technological regression, with few airports achieving increased productivity-led efficiency improvements. They examine efficiency gains in Italian airports considering the transformation experienced by the Italian airport industry during the period 2000-2006, studying the impact of factors such as airside activities, private-capital inflows, types of concession agreements and liberalization of handling services. They find that private-capital inflows are a source of efficiency improvements. In another paper, Gitto et al. (2013) focus on quality management of Italian airports. They apply a DEA Malmquist index, which includes a quality component, to assess the impact of the quality of the services delivered by an airport on its productive performance and find that the quality of Italian airports is acceptable in relation to their infrastructure, but that managerial procedures require improvements to satisfy customer demands (De Nicola et al., 2013).

The Italian airport business system has some specific characteristics which have been identified in recent studies. For example, Nucciarelli and Gastaldi (2009) point to key opportunities for Italian airports based on growth driven by investment in new technologies to foster collaboration within the airport industry.

Barros and Dieke (2008) apply the two-stage procedure proposed by Simar and Wilson (2007) to estimate the efficiency of Italian airports between 2001 and 2003 and to overcome the limitations in classical application of DEA to study of airport efficiency. Other authors followed a similar approach and apply DEA two stage procedure. For example, Curi et al. (2010) analyse the impacts of Italian government actions, such as privatisation, enlargement of the services provided directly by airport management companies, through the modification of the concession agreements, and the creation of two hubs on the efficiency of 36 airports between 2001 and 2003 and find that airports with a majority public holding are on average more efficient and the presence of two hubs is source of inefficiency. Adler and Liebert (2014) seek to assess the combined impact of the environmental variables, such as ownership and regulation form, in order to gain understanding as to the most efficient ownership form and regulatory framework whilst accounting for levels of regional and hub competition. They find that unregulated major and fully private airports located in a competitive setting pursue profit maximization than regulated airports of the same ownership structure. Merkert and Mangia (2014) a two-stage DEA approach, with truncated regression models in the second stage to benchmark Italian and Norwegian airports to evaluate the role of competition as a key determinant of the first stage efficiency scores. Kung-Tsu et al. (2014) evaluate the operational efficiency of 21 Asia-Pacific airports using the two stage method and identify the key factors to explain variations in airport efficiency. Four significant factors were identified, (i) more international passengers handled by an airport that may reduce its efficiency level; (ii) when an airport caters to a larger hinterland population, it will become less efficient than an airport that serves a smaller hinterland population; (iii) if the dominant airline(s) of an airport enters a global airline strategic alliance, this may improve its home-based airport's efficiency; and (iv) having an increase in GDP per capita of a country or city might increase an airport's efficiency. Zou et al. (2015) apply the two stage DEA procedure to investigate the effect on airport productivity efficiency of two funding sources used in the US and find that only one of the two has a positive impact on airport productive efficiency. Örkcü et al. (2016) study the efficiency and productivity of Turkish airports and show that there has been a significant decline in their efficiency during the period 2011-2012 because the significant increase in the physical capacity has not been followed by an increasing physical capacity to passenger and cargo traffic.

Recently, Fragoudaki and Giokas (2016) find scope for substantial efficiency improvement in Greek airports. Specifically, they find that the island location, connectivity and hotel infrastructure positively affect airports' performance. Wanke et al. (2016) show that Nigerian airports would benefit from combining third-party capacity management, such as privatization, and continuous improvement practices. Liu (2016) analyses East Asia airports and finds that aeronautical service efficiency is positively impacted by the number of airlines served and destinations, while non-aeronautical revenues and service quality have a significant ad positive impact on commercial efficiency.

As shown by the review of the literature, our variable of interest, the development of HSR and the relation between HSR services and airport systems within a geographical region has not been investigated. Indeed, the analysis of potential interaction among the infrastructures would lead to better management of airport systems. The topic is interesting also because many European countries invested in HSR during the last decade, in order to improve the countries' transportation system. For this reason, the present paper investigates the impact of development of HSR services on the airport systems in Italy and provides insights for policy makers.

Table 1. Summary of literature on DEA and airport efficiency (in chronological order)

Research	Method	Sample size	Year (s)	Inputs	Outputs
Gillen and Lall (1997)	DEA-BCC model and a Tobit model	21		*(i) Terminal services model:* 1. number of runways, 2. number of gates 3. terminal area, 4. number of baggage collection belts *(ii) Movement model:* 1. airport area, 2. number of runaway, 3. runaway area, 4. number of employees	*(i) Terminal services model:* 1. number of passengers, 2. pounds of cargo *(ii) Movements model:* 1. air carrier movements, 2. commuter movements
Parker (1999)	DEA-BCC model and CCR model	32	1979-1996	1. Number of employees, 2. capital input estimated as an annual rental based on a real rate of return of 8% each year applied to net capital stock, 3. other inputs defined as the residual of total operating costs	1. Turnover, 2. passengers handled, 3. cargo and main business
Gillen and Lall (2001)	DEA-Malmquist	22	1992-1994	*(i) Terminal services model:* 1. number of runways, 2. number of gates, 3. terminal area, 4. number of employees, 5. number of baggage collection belts, 6. number of public parking places *(ii) Movement model:* 1. airport area, 2. number of runways, 3. runway area, 4. number of employees	*(i) Terminal services model:* 1. number of passenger, 2. number of pounds *(ii) Movement model:* 1. air carrier movements, 2. commuters movements
Murillo-Melchor (1999)	DEA-Malmquist	33	1992-1994	1. Number of workers, 2. accumulated capital stock proxied by amortization, 3. intermediate expenses	Number of passengers
Sarkis (2000)	Several DEA models, including CCR and BCC models	43	1990-1994	1. Operating costs, 2. employees, 3. gates,	1. Operating revenues, 2. aircraft movements, 3. general aviation

				4. runaways	4. total passengers 5. total freight
Pels et al. (2001)	DEA-BCC model	34	1995-1997	1. Terminal size in square meters, 2. number of aircraft parking positions at the terminal, 3. number of remote aircraft parking positions, 4. number of check-in desks, 5. number of baggage claims	(i) Terminal model: 1. Number of passengers (ii) Movement model: 1. aircraft transport movement
Pels et al. (2003)	DEA-BCC model and Stochastic Frontier Analysis			*(i) Terminal model:* 1. Airport surface area, 2. number of air- craft parking positions at terminal, 3. number of remote aircraft parking positions, 4. number of runways, 5. dummy z variables for slot-coordinated airports, 6. dummy z variable for time restrictions *(ii) Movement model:* 1. number of check-in-desks, 2. number of baggage claim units, 3. annual number of domestic and international movements	*(i) Terminal model:* 1. annual number of domestic, 2. international movements *(ii) Movement model:* 1. annual number of domestic, 2. international passengers
Adler and Berechman (2001)	DEA-BCC with principal component analysis	26		1. Passenger terminals, runways, 2. distance to city centres, 3. minimum connecting times in a minute	1. Principal component obtained from a questionnaire on airlines
Sarkis and Talluri (2004)	DEA-CCR and cross-efficiency DEA model from Doyle and Green (1994)	43	1990-1994	1. Operating costs, 2. employees, 3. gates, 4. runaways	1. operating revenue 2. aircraft movements 3. general aviation 4. total passengers 5. total freight
Barros and Sampaio (2004)	DEA-allocative model	10	1990-2000	1. Number of employees 2. capital proxied by the book value of physical assets, 3. price of capital, 4. price of labour	1. number of planes 2. number of passengers 3. general cargo 4. mail cargo 5. sales to planes 6. sales to passengers

Yoshida and Fujimoto (2004)	DEA-CCR, DEA-CCR and input distance function	43	2000	1. runaway length 2. terminal size 3. monetary access cost 4. time access cost 5. number of employees in terminal building	1. passenger loading 2. cargo handling 3. aircraft movement
Barros and Dieke (2007)	Cross- efficiency DEA model and Super-efficiency DEA model	31	2001-2003	1. Labour cost, 2. capital invested, 3. operational costs excluding	1. Number of planes, 2. number of passengers 3. general cargo, 4. handling receipts, 5. aeronautical sales, 6. commercial sales
Barros and Dieke (2008)	DEA - Simar and Wilson two-stage procedure	31	2001-2003	1. Labour costs, 2. capital, invested 3. operational costs, excluding labour costs	1. Number of planes, 2. number of passengers 3. general cargo, 4. handling receipts, 5. aeronautical sales, 6. commercial sales
Fung et al. (2008)	Malmquist- DEA model	25	1995-2004	1. runaway length 2. terminal size	1. passengers handled 2. cargo handled 3. aircraft movement
Curi et al. (2010)	DEA – Two stage analysis	36	2001-2003	1. labour costs, 2. capital invested 3. operational costs excluding labour costs	4. number of planes and passengers, 5. tons of cargo, 6. aeronautical sales, 7. handling receipts 8. commercial sales
Yu (2010)	Slacks-based measure network data envelopment analysis (SBM-NDEA)	15	2006	*Variable input:* 1. Labour *Quasi fixed inputs:* 2. runway area, 3. apron area 4. terminal area	*Airside outputs:* 1. Movements *Landside outputs:* 1. Passengers 2. Cargo
Curi et al. (2011)	Bootstrapping DEA	18	2000-2004	1. Airport area 2. labour cost 3. other costs	1. aeronautical revenue 2. non-aeronautical revenue
Gitto and Mancuso (2012b)	DEA – Two models	28	2000-2006	*(i) Monetary model:* 1. labour cost, 2. capital invested 3. soft costs *(ii) Physical model:* 1. number of workers,	*(i) Monetary model:* 1. aeronautical revenues 2. non-aeronautical revenues *(ii) Physical model:* 1. number of movements, 2. number of passengers

				2. runway area, *3.* airport area	3. amount of cargo
Gitto and Mancuso (2012a)	DEA – Malmquist	28	2000-2006	1. Labour cost 2. Capital invested 3. Soft cost	1. number of passengers, 2. the amount of cargo, 3. number of aircraft movements, 4. aeronautical revenues 5. non-aeronautical revenues
De Nicola et al. (2013)	DEA – Malmquist	20	2006-2008	4. Labour cost 5. Capital invested 6. Soft cost	7. Number of movements 8. Work load units
Merkert and Mangia (2014)	DEA – two stage approach, with truncated regression models in the second stage	35 Italian and 46 Norwegian airports	2007-2009	*Inputs – technical*: 1. Terminal area 2. apron area 3. number of runway 4. runway length 5. runway area 6. total area 7. no. of employees *Inputs – financial* 1. Operating cost 2. staff cost 3. material cost	*Outputs – traffic:* 1. Air traffic movements 2. passengers 3. cargo
Coto-Millan et al. (2014)	DEA and regression analysis	35	2009-2011	1. Labour cost, 2. capital invested 3. other expenses	1. The number of cargo, the 2. number of passengers, 3. amount of cargo, 4. number of aircraft movements
Kan Tsui et al. (2014)	DEA two stage method	21	2002-2011	1. Number of employees, 2. number of runaways, total runaway length, 3. passenger terminal area	1. Air passenger numbers, 2. air cargo volumes, 3. aircraft movements
Adler and Liebert (2014)	DEA two stage method	48	1998-2007	1. Staff costs, 2. other operating costs, 3. declared runaway capacity	1. Passengers, 2. cargo, 3. air transport movements, 4. non-aeronautical revenues
Gitto and Mancuso (2015)	DEA - Malmquist	20	1980-2006	1. Labour, 2. capital, 3. time	
Zou et al. (2015)	DEA – CCR/BCC – Two stage	42	2009-2012	1. labour cost, 2. materials cost, 3. capital cost	1. passenger enplanements, 2. aircraft operations, 3. amount of cargo handled, 4. non-aeronautical revenue,

					5. total flight arrival delay minutes
Fragoudaki and Giokas (2016)	Two stages, DEA, Mann–Whitney U and Kruskal–Wallis tests and Tobit regression	38	2009-2011	1. Airport infrastructure measures such as runway length in meters, 2. apron size in square meters, 3. passenger terminal size in square meters	1. Annual data for total aircraft movements, 2. total numbers of passengers, 3. tons of cargo handled
Liu (2016)	Network DEA	10	2009-2013	*Input variables in the first sub-process:* 1. runaway area 2. staff costs 3. other operating costs	*Output variables in the second sub-process:* *1.* passengers and cargo 2. operating revenues
Örkcü et al (2016)	DEA and Malmquist productivity index; Simar-Wilson double bootstrapping regression analysis	21	2009-2014	1. Number of runway, 2. dimension of runaway units 3. passenger terminal area	1. annual number of flights, 2. annual passenger throughputs, 3. annual cargo throughputs
Wanke et al. (2016)	Fuzzy DEA	30	2003-2013	1. Terminal capacity (number of passengers/year), 2. runway dimension (sq. meters), 3. number of employees, 4. apron area (sq. meters)	1. Number of passengers (per year), 2. numbers of movements (landing and take-offs per year), 3. cargo throughput (kg/year), 4. mail throughput (kg/year)

Figure 1 shows the current situation in Italy in relation to the distribution of airports and HSR stations across the country.

Figure 1. Distribution of airports and HSR stations in the Italian territory

2. Data and Methodology

To estimate the influence of HSR on technical efficiency we propose a two stage estimation which implements DEA to obtain airport efficiency scores and regresses them with the variables of interest (Simar and Wilson, 2007). Although DEA is more sensitive to outliers and more time consuming, we consider it appropriate to estimate airport efficiency since the technological frontier is based on a multiple input and output framework and it is not constrained by a functional form. Throughout this analysis we use an output oriented approach for two reasons. Firstly, it is widely preferred in past works on airport efficiency; moreover it is more credible for management to change output than input used in the analysis.

In its most basic formalization, DEA hypothesizes Constant Returns to Scale (CRS) for the production function (Charnes et al., 1978). Banker et al. (1984) extended the model to include

Variable Returns to Scale (VRS). Thus, it is not always possible to replicate the best combination of inputs and outputs to infinity. In its most refined form, the problem of linear programming is solved as follows:

$$
\begin{aligned}
& Max\ \delta\ subject\ to \\
& \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{i0} \qquad i = 1,2, \dots, m; \\
& \sum_{j=1}^{n} \lambda_j y_{rj} \leq \delta y_{r0} \qquad r = 1,2, \dots, s; \\
& \sum_{j=1}^{n} \lambda_j = 1 \\
& \lambda_j \geq 0 \quad j = 1,2, \dots, n.
\end{aligned} \tag{1}
$$

This DEA formulation is deterministic and is a limitation in relation to inferences and estimation of the frontier. To overcome this, Simar and Wilson (1998) introduced an unbiased bootstrap replication, which enables inferences starting from a real distribution. They show that naïve bootstrap is inconsistent and propose smoothed bootstrap to correct the scores. They also suggest implementing m out of n bootstrap inferencing based on DEA scores, and developed an inference test for returns to scale. They test whether the estimated frontier has CRS or VRS (Simar and Wilson, 2011a, 2002) using the formula below:

$$\hat{\tau}_3(S_n) = n^{-1} \sum_{i=1}^{n} \left(\frac{\hat{\delta}_{CRS}(x_i, y_i|S_n)}{\hat{\delta}_{VRS}(x_i, y_i|S_n)} -1 \right) \geq 0 \qquad (2)$$

By repeating B times for subsamples drowned by m out of n bootstrap, we obtain the set S_n. This sample allows the construction of confidence intervals to test the statistics. The closer to zero, the higher the probability that VRS are equal t. Simar and Wilson assume H_0: is that the frontier presents CRS.

All those factors not under managerial control are defined as environmental variables and can be introduced in DEA using various methods. Banker and Morey (1986) propose adding environmental variables in the linear programming calculus as non-discretionary inputs or outputs. Daraio and Simar (2005) disagree on the basis that there are no reasons to decide ex-ante whether the effect of the variables on efficiency is a discretionary input or output. The most popular application is truncated regression of efficiency scores as the dependent variable with environmental independent variables. However, this method has been show to produce biased results (Simar and Wilson, 2011b). A semiparametric regression procedure was introduced to generate unbiased estimate (Simar and Wilson, 2007), and this is the methodology employed here. Simar and Wilson proposed two alternative algorithms, using a double bootstrap procedure to correct the bias generated by estimation of DEA scores, and the relationship of the environmental variables to the DEA scores. Their approach is summarized in the following steps:

Using (1) compute $\widehat{\delta_i} = \hat{\delta}\left(x_i, y_i \middle| \widehat{\mathbb{P}}\right) \forall\ i = 1,2,\ldots,n$ airport observations.

Estimate $\hat{\beta}$ and $\hat{\sigma}$ of the truncated regression $\delta_i = Z_i\beta + \varepsilon_i$ using the method of maximum likelihood (ML) using m out of n inefficient observations such that $\widehat{\delta_i} > 1$.

Repeat steps *a* to *d* B_1 times. We obtain the set of bootstrap $B_i = \{\widehat{\delta_{ib}^*}\}_{b=1}^{B_1}$.

a $\forall\ i = 1, 2, \ldots, n$ estimate ε_i from distribution $N(0,\widehat{\sigma_\varepsilon^2})$ truncated on the left at $(1 - Z_i\hat{\beta})$.

b $\forall\ i = 1, 2, \ldots, n$ compute $\delta_i^* = Z_i\hat{\beta} + \varepsilon_i$.

c Transform the original outputs $x_i^* = x_i, y_i^* = y_i(\widehat{\delta_i}/\delta_i^*)\ \forall\ i = 1, 2, \ldots, n$.

d Compute $\hat{\delta}_i^* = \hat{\delta}\left(x_i, y_i \middle| \widehat{\mathbb{P}}^*\right) \forall\ i = 1,2,\ldots,n$, $\widehat{\mathbb{P}}^*$ results of replacing $Y^* = \left[y_1^*, \ldots, y_n^*\right], X^* = \left[x_1^*, \ldots, x_n^*\right]$ to Y and X.

Compute the bias corrected estimates $\hat{\hat{\delta}}_i = \hat{\delta}_i$-$\widehat{BIAS}(\hat{\delta}_i)$ using bootstrap estimates $B_i$of point 3.*d* and the original estimates in 1.

Estimate $\hat{\hat{\beta}}$ and $\hat{\hat{\sigma}}$ of the truncated regression $\hat{\hat{\delta}}_i = \beta_i Z_i + \varepsilon_i$ using ML.

Repeat steps a to c B_2 times to generate the bootstrap sample $C_i = \{\hat{\beta}^*, \hat{\sigma}_\varepsilon^*\}_{b=1}^{B_2}$.

a $\forall\ i = 1, 2, \ldots, n$ estimate ε_i from distribution $N(0,\widehat{\widehat{\sigma_\varepsilon^2}})$ truncated on the left at $(1 - Z_i\hat{\hat{\beta}})$.

b $\forall\ i = 1, 2, \ldots, n$ compute $\delta_i^{**} = z_i\hat{\hat{\beta}} + \varepsilon_i$.

c Estimate $(\hat{\hat{\beta}}^*, \hat{\hat{\sigma}}^*)$, of the truncated regression $\delta_i^{**} = Z_i\beta + \varepsilon_i$ using ML.

Construct the confidence intervals for β's and σ_ε using the bootstrap sample C_i and the original estimates $\hat{\hat{\beta}}$ and $\hat{\hat{\sigma}}$.

To implement this algorithm we used the R package (rDEA).

The data employed in our empirical analysis and their descriptive statistics are reported in Table 2. The airports considered in the analysis are those included in the Piano Nazionale degli Aeroporti (National Airport Plan) released by the Italian Ministry for Infrastructures in September 2014. Input, output and exogenous variables are relative to the period 2004-2013 for a total of 258 observations.

Airports are indexed by their IATA code. In the cases of Milan Linate and Malpensa (IATA codes LIN and MXP) and Rome Fiumicino and Ciampino (IATA codes FCO and CIA), which are managed respectively by SEA and Aeroporti di Roma, only aggregated data on employees are available. For these two cases, data on employees, traffic, facilities, etc. are aggregated in two entities denominated under the IATA codes MIL and ROM.

To analyse airport efficiency and the influence of HSR, we use a general framework with two output and two inputs. On the input side, the main variables employed are each airport company's number of employees and number of runways. The variable for number of employees is from the AIDA database {van Dijk, 2013 #75} (Analisi Informatizzata delle Aziende, Bureau van Dijk); data on the number of runways are from the Atlante degli Aeroporti Italiani (Atlas of Italian Airports).

For outputs, we use the variables number of takeoffs and landings (mov) or number of passengers (pax) and cargo tonnages (cargo) processed. For the passengers variable, we considered national and international flights (paxnat and paxintl) and numbers of passengers transported by low cost carriers (paxlow) and by traditional flag carriers (paxflag). All data on passengers are from Dati di Traffico degli Scali Italiani (Traffic Data of Italian Airports) published by ENAC, the Italian civil aviation authority. Data on the percentage of passengers processed by low cost carriers are not available for the years 2004, 2005 and 2007; where this variable is used as either a control or an output, the sample is restricted to 2006 and 2008-2013, with a contraction in the original sample from 258 to 185.

The Simar-Wilson regression includes a series of controls for endogeneity stemming from missing variables. Environmental effects are represented by dummy variables for an airport location in the north, centre or south of Italy, using the logarithm of regional (NUTS-2) population (lpop), and per capita regional gross domestic product (lgdppc) published by the Italian National Statistics Institute (ISTAT). Time varying general conditions are controlled for by the inclusion of either a time trend or f year fixed effects dummies, which are activated if the observation is relative to the specific year. Controls for airport size are represented by dummies that activate if the airport is considered in the 2014 National Airport Plan as "strategic" or "strategic international".

Finally, the interest variable in the efficiency scores regressions consists of an index for the presence of HSR in the region of the airport (hsr). The variable is coded as a binary variable which activates if there is a HSR station in the region of the airport in the year of reference, multiplied by the length of the high speed network in the country. This composite variable should capture both the effect of an HSR link in the vicinity of the airport and the importance of this link in terms of time gains provided by the high speed network as a whole. The data used to build this variable are from RFI (the owner of the Italian rail network). To calculate the length of the high speed network, we consider a line as active and include it in our variable only from its first full year of operation; partial openings are excluded on the grounds of the limited amount of detailed information provided by RFI.

Table 2. Descriptive statistics

Variable	Type	Unit	Obs	Mean	Median	Std Dev	Min	Max
Employees	Input	number	257	344	213	555	22	2770
Runways	Input	number	257	1	1	1	1	5

Pax	Input	number	257	4964625	1989130	8644521	18355	42183018
Pax National	Input	number	257	2042947	1146979	2869691	38	14016809
Pax Intl	Input	number	257	2662813	601581	5716671	21	28267517

YEAR	2004	2005	2006	2007	2008

Cargo	Input	tons	257	31446	2034	88720	1	470040
HSR	Interest	km	257	309	0	433	0	943
Lowcost	input/control	percentage	185	43	37	27	0	97
Population	Control	number	257	3949018	4090266	2315434	313341	9973397
GNPpercapita	Control	euro	257	22803	24900	6057	14383	36300
North	Control	binary	257	0.41	0	0.49	0	1
Centre	Control	binary	257	0.30	0	0.46	0	1
Strategic	Control	binary	257	0.47	0	0.50	0	1
Strategic intl	Control	binary	257	0.11	0	0.32	0	1

IATA CODE	Score	Lo	Up	Score	Lo	Up	Score	Lo	Up	Score	Lo	Up	Score	Lo	Up
AHO	3.856	3.583	4.014	3.864	3.567	4.011	4.389	4.060	4.571	4.283	3.964	4.509	5.040	4.688	5.444
AOI	3.373	3.140	3.544	9.319	8.240	####	3.850	3.601	4.029	4.021	3.732	4.258	4.330	3.991	4.576
BDS	1.116	1.062	1.173	2.009	1.938	2.072	1.483	1.424	1.538	1.311	1.256	1.359	2.199	2.108	2.255
BGY	1.248	1.085	1.433	1.283	1.116	1.466	1.243	1.090	1.397	1.260	1.099	1.393	1.241	1.059	1.405
BLQ	2.288	2.020	2.491	1.813	1.584	1.973	1.563	1.352	1.706	1.631	1.409	1.792	1.456	1.248	1.623
BRI	2.073	1.929	2.166	3.637	3.366	3.904	2.410	2.233	2.534	2.009	1.861	2.112	3.033	2.809	3.286
CAG	1.759	1.627	1.839	1.905	1.766	2.006	1.932	1.790	2.041	1.835	1.700	1.936	1.822	1.685	1.932
CTA				1.376	1.285	1.445	1.328	1.248	1.393	1.182	1.119	1.237	1.187	1.124	1.243
ROM	1.450	1.263	1.596	1.346	1.167	1.481	1.266	1.097	1.390	1.135	0.977	1.246	1.223	1.026	1.355
FLR	4.956	4.594	5.277	4.261	3.958	4.469	4.606	4.331	4.739	3.659	3.461	3.765	3.632	3.420	3.735
GOA	7.035	6.558	7.616	7.051	6.570	7.576				6.717	6.223	7.202	3.884	3.601	4.059
MIL	1.528	1.285	1.787	1.474	1.239	1.726	1.343	1.127	1.571	1.292	1.110	1.511	1.500	1.285	1.755
LMP															
NAP	1.536	1.439	1.594	1.548	1.469	1.605				1.229	1.167	1.269	1.248	1.185	1.281
OLB	4.611	4.333	4.780	4.392	4.110	4.551	3.992	3.741	4.130	4.098	3.834	4.278	4.082	3.803	4.251
PEG										6.211	5.804	6.620			
PMF							1.511	1.183	1.945						
PMO	2.232	2.118	2.325	1.642	1.573	1.696	2.971	2.676	3.147	2.757	2.485	2.916	2.888	2.592	3.059
PNL															
PSA							3.721	3.379	4.047	3.307	2.991	3.597	4.433	3.990	4.823
PSR	2.048	1.926	2.156	1.891	1.778	1.998	2.099	1.962	2.217	2.160	2.029	2.273	2.607	2.451	2.731
REF							3.393	3.256	3.479	2.813	2.716	2.900	3.054	2.945	3.151
RMI	5.747	5.407	6.016	6.562	6.138	6.890	6.250	5.859	6.507	4.487	4.206	4.650	4.432	4.161	4.608
SUF				5.703	5.280	6.171	4.909	4.557	5.304	5.161	4.807	5.588	5.070	4.707	5.475
TFS				1.144	1.068	1.203	1.498	1.381	1.593	1.575	1.452	1.673	1.695	1.588	1.767
TPS							8.895	8.221	9.195	4.002	3.702	4.141	2.621	2.432	2.729
TRN	2.255	2.098	2.435	2.449	2.286	2.664	2.344	2.184	2.557	2.145	1.991	2.317	2.130	1.971	2.250
TRS	6.625	6.093	6.884	7.032	6.468	7.307	6.702	6.183	6.984	6.181	5.701	6.426	5.041	4.683	5.227
VBS	4.562	4.335	4.732	2.159	1.882	2.384	2.138	1.882	2.406	1.259	1.126	1.390	1.531	1.322	1.749
VCE				1.230	1.144	1.301	1.129	1.049	1.195	1.976	1.769	2.105	2.326	2.087	2.549
VRN	2.671	2.539	2.738	2.702	2.566	2.770	2.417	2.286	2.522	2.005	1.910	2.049	2.069	1.975	2.118
mean	3.148			3.241			3.053			2.918			2.806		
S.D.	1.798			2.264			1.934			1.668			1.296		
max	7.035			9.319			8.895			6.717			5.070		
min	1.116			1.144			1.129			1.135			1.187		

Table 3. DEA scores with confidence intervals for model1

Continued

YEAR	2009			2010			2011			2012			2013		
IATA CODE	Score	Lo	Up	Score	Lo	Up	Score	Lo	Up	Score	Lo	Up	Score	Lo	Up
AHO	4.033	3.772	4.295	5.214	4.838	5.486	4.759	4.437	4.998	4.738	4.456	4.967			
AOI	5.426	5.011	5.766				3.654	3.373	3.866	4.134	3.813	4.388	4.313	3.975	4.592
BDS	1.904	1.826	1.951	1.646	1.581	1.684	1.345	1.294	1.376	1.276	1.227	1.306	1.323	1.272	1.354
BGY	1.324	1.119	1.462	1.239	1.048	1.367	1.218	1.035	1.335	1.259	1.088	1.382	1.202	1.030	1.316
BLQ	1.392	1.186	1.552	1.273	1.080	1.426	1.194	1.020	1.335	1.175	0.997	1.312			

BRI	2.559	2.385	2.693	2.139	1.989	2.252	1.922	1.785	2.005	1.884	1.764	1.959	1.967	1.841	2.038
CAG	1.712	1.593	1.813	1.680	1.567	1.780	1.490	1.380	1.569	1.550	1.437	1.634			
CTA	1.239	1.152	1.317	1.192	1.104	1.289	1.132	1.056	1.232	1.243	1.160	1.350	1.203	1.121	1.314
ROM	1.284	1.078	1.437	1.197	1.008	1.320	1.162	0.973	1.298	1.273	1.113	1.494	1.362	1.216	1.608
FLR	4.166	3.887	4.305	4.087	3.813	4.230	3.736	3.493	3.853	3.827	3.580	3.945	3.568	3.346	3.673
GOA	6.594	6.127	7.061	5.617	5.216	5.872	5.126	4.793	5.349	5.224	4.892	5.458	5.561	5.194	5.842
MIL	1.563	1.345	1.748	1.325	1.104	1.510	1.273	1.060	1.438	1.376	1.167	1.539	1.333	1.111	1.500
LMP													3.946	3.709	4.191
NAP	1.323	1.258	1.357	1.259	1.197	1.290	1.217	1.158	1.246	1.211	1.150	1.241	1.311	1.241	1.359
OLB	4.356	4.061	4.514	4.446	4.147	4.616	3.898	3.628	4.049	3.852	3.585	4.001	3.587	3.341	3.732
PEG				6.845	6.416	7.297	4.872	4.586	5.168						
PMF							1.749	1.592	1.934						
PMO	2.911	2.612	3.081	2.844	2.560	3.010	2.502	2.248	2.647	2.702	2.429	2.859	2.878	2.584	3.046
PNL							3.765	3.467	4.084	6.353	6.016	6.699	6.891	6.546	7.224
PSA	4.267	3.779	4.679	4.225	3.742	4.639	3.784	3.353	4.160	3.811	3.376	4.184	3.766	3.309	4.114
PSR	2.728	2.553	2.843	3.056	2.873	3.178	2.568	2.439	2.671	1.864	1.776	1.952	1.732	1.630	1.825
REF	3.257	3.138	3.363	3.162	3.050	3.262	3.128	3.011	3.225						
RMI	6.089	5.679	6.318	4.611	4.270	4.773	3.103	2.880	3.208	4.002	3.730	4.146			
SUF	4.473	4.142	4.724	3.815	3.530	4.029	3.094	2.925	3.204	3.197	3.040	3.300	3.240	3.075	3.345
TFS	1.874	1.743	1.942	2.100	1.946	2.197	3.516	3.279	3.648	2.128	1.971	2.229			
TPS	1.775	1.646	1.839	1.481	1.367	1.529	1.638	1.511	1.693	1.606	1.483	1.659	1.327	1.224	1.370
TRN	2.224	2.072	2.322	2.002	1.863	2.081	1.911	1.783	1.983	2.015	1.878	2.088	2.247	2.092	2.335
TRS	6.222	5.721	6.466	5.968	5.487	6.201	4.420	4.107	4.583	4.406	4.096	4.567	4.612	4.284	4.781
VBS	2.253	1.978	2.528	2.177	1.885	2.441	2.937	2.534	3.305	1.941	1.691	2.208			
VCE	2.394	2.148	2.626	2.324	2.088	2.548	1.922	1.726	2.093	1.988	1.787	2.173	1.906	1.715	2.091
VRN	2.340	2.197	2.419	2.334	2.228	2.390	1.803	1.679	1.912	1.912	1.779	2.029			
mean	3.025			2.935			2.661			2.665			2.823		
S.D.	1.622			1.630			1.242			1.434			1.580		
max	6.594			6.845			5.126			6.353			6.891		
min	1.239			1.192			1.132			1.175			1.202		

Table 3 summarises efficiency results by airport and year. In the first column we can observe IATA codes that identify univocally Italian airports. For each year, we have three columns. In the first we have the unbiased efficiency score in the second and third there are lower (Lo) and upper (Up) bounds of 95% confidence intervals. Results are available from 2004 to 2013, empty spaces are due to a lack of data for that year and airport. For each year descriptive statistics of the scores are provided at bottom of the table. Average efficiency scores range from 2.661 to 3.241, across years. Although the sample changes, due the presence of missing data, average efficiency scores seem to be rather stable. Similarly, standard deviation is quite stable across years. Figure 2 illustrates the unbiased score ordered by latitude (from North to South). Results show that airport based in northern Italy are more efficient than those in the south and standard deviation in results are smaller. Figure 3 displays results by airport dimension from the larger (on the left) to the smaller. Also in this case unbiased efficiency scores are smaller (more efficient) for larger production units. Further, efficiency scores for larger airport have a lower standard deviation among results compared with smaller ones.

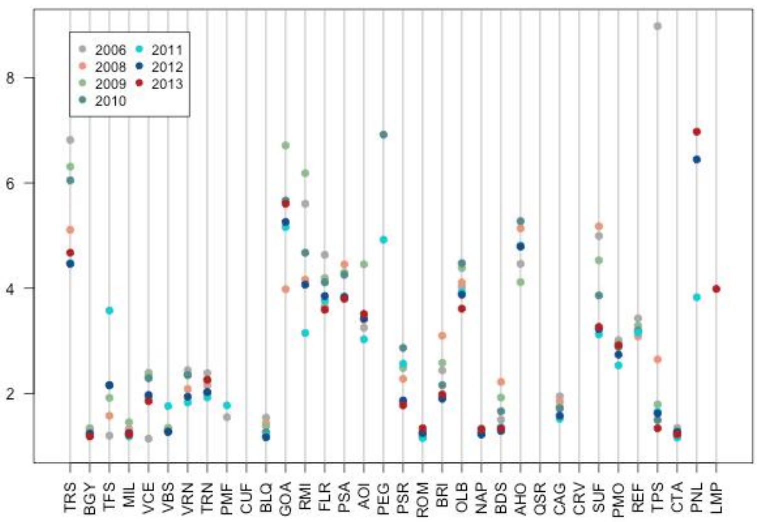

Figure 2. Unbiased score ordered by latitude

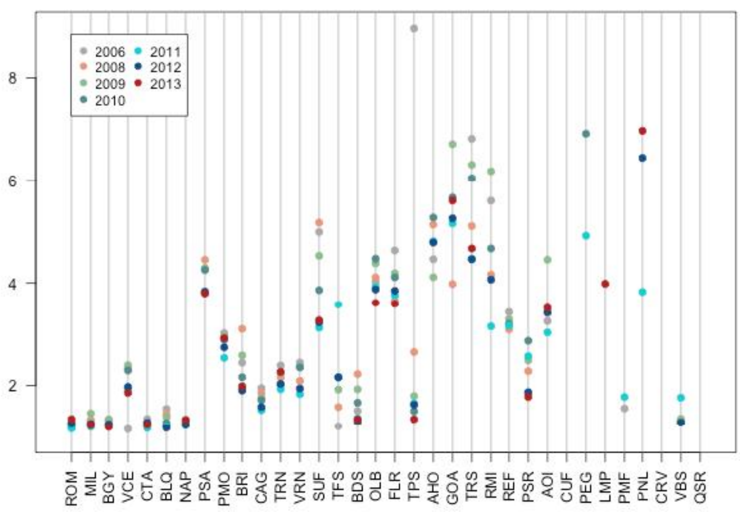

Figure 3. Unbiased score ordered by dimension

In the first stage we compute nonparametric efficiency scores with different inputs and outputs configurations. In the second stage the scores from the first stage are regressed on a series of covariates.

In the main model in our analysis, nonparametric estimation of efficiencies is performed on two inputs (employees and runways which proxy for labour and capital factors respectively) and two outputs (passengers and cargo, the main objectives of airport activity). The number of inputs and outputs is kept low in order to deal with the problem of dimensionality typical of nonparametric estimations. The choice of variables is consistent with previous analyses (Curi, Gitto and Mancuso 2011, Pels, Nijkamp and Rietveld 2003) and should be sufficient to strike a balance between the analytical detail and the accuracy losses due to dimensionality (see Simar and Wilson 2008). The second stage truncated regression in Simar and Wilson (2007) is specified using different configurations of covariates, with hsr as the variable of interest and modifying the set of control variables. In particular, in this specification, the variable for the share of passengers transported by low cost carriers is introduced explicitly as a conditioning variable. In order to address any deficiencies of the main model detailed above, we perform two robustness checks where the set of output variables in our efficiency score analysis is modified.

In the first robustness check, the percentage of low cost passengers processed by airports is introduced as an output of the DMU activity in the first stage of the analysis, rather than as an environmental variable in the second stage. Therefore, in this model inputs are the same as in the main model, while the set of outputs is composed of three elements: the percentage of passengers transported by flag carriers (pax_flag); the percentage transported by low cost carriers (pax_low); and tonnage of cargo. The inclusion of a distinction between flag carrier and low cost carrier passengers is justified by the fact that DMU managers might not be completely passive and might choose the proportions between different types of vectors. Of course, the percentage of low cost passengers is not included in the second stage regressions.

The second robustness check deals with the possibility that HSR transport could have different impacts on airports depending on whether they specialize in short distance or long distance connections. Here, inputs remain the same as in the previous models, but the output set is modified in order to distinguish between cargo, national (pax_nat) and international (pax_intl) flights.

2. Empirical results

Table 4 presents the results of a series of regressions of the reciprocals of the efficiency scores, ranging from 1 to infinity. Including the variable for the percentage of low cost carriers reduces the sample size from 258 to 185 observations. In all cases, the Simar and Wilson test rejects the null hypothesis of CRS at the 1% size in both formulations (2002 and 2011).

The effect of the presence of an HSR link in the region is always positive for the efficiency score (negative for its reciprocal). The coefficient tends to decrease when the controls are included, but its sign remains constant and significant at below 1% even in the most general specification (with low cost and year fixed effects added).

Table 4 presents the results for evaluation of the effect of an increase of 100km, 200km and 500km of HSR network for airports with a station in the region based on the coefficient estimated in the most general specification. The coefficient representing the effect of low cost air carriers seems to be robust to the inclusion of covariates. Its negative sign suggests a positive effect on efficiency. Among the other control variables, it is worth noting that strategic airports and, specifically, strategic international airports, seem to be more efficient even after controlling for the presence of VRS in the computation of efficiency scores, while the geographical location of the airport seems to have no impact on their efficiency once the effects of the other variables are controlled for.

Table 4. Regressions with efficiency score of model 1 as dependent variable.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
HSR	-0.0060***	-0.0042***	-0.0018	-0.0013**	-0.0018**	-0.0017***
Lowcost		-0.0645***		-0.0478***		-0.0492***
Trend			-0.0402	0.0247		

North			-1.8033	-1.2199	-2.2444*	-2.0147
Centre			-0.7613	0.4236	-1.0354	0.0225
Strategic			-1.2600**	-1.4042**	-1.2473***	- 1.3245***
Strategic intl			-9.7981***	-8.3666***	-9.5900***	-8.3412***
Log Population			-1.9779***	-1.0850***	-2.0267***	-1.0679***
log GNPpercapita			5.1980***	3.2491	5.8868***	4.7177
Year fixed effects					Yes	Yes
Constant			-1.9249	2.7362**	61.6202	-60.9593
Obs	257	185	257	185	257	185

*** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$.

Table 5. Regressions with efficiency score of model 3 as dependent variable.

	(1)	(2)
HSR	-0,1214***	-0,0212***
Low		
Trend		-0,4137***
North		-21,4749***
Centre		-13,4500**
Strategic		-19,5478***
Strategic intl		-136,6886***
Log_pop_region		-7,2875***
Log_gdp_pc_regio		67,2898***
Year fixed effects		
Constant	-121,3376***	246,5316**
Obs	257	257

*** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$.

Table 6. Regressions with efficiency score of model 2 as dependent variable.

	(1)	(2)	(3)
HSR	-0,0045***	-0,0014***	-0,0012**
Trend		-0,0444	
North		-0,5492	-0,1385
Center		-0,6870	-0,4605
Strategic		-1,1986*	-1,2615*
Strategic intl		-5,6507***	-5,4231***
Log Population		-1,6099***	-1,5944***
Log GNPpercapita		3,4117	2,6149
Year fixed effects			yes
Constant	-1,1928	81,5449	-0,0150
Obs	185	185	185

*** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$.

Before performing the first and second stage estimations of our models, we test for the presence of CRS in our frontier. In all input-output configurations, the evidence shows that Simar and Wilson tests reject the null hypothesis of CRS against the alternative of VRS at the 1% significance level in both formulations (2002 and 2011). The results of these tests might appear at odds with previous evidence for Italian airports of CRS, for example, as Barros and Dieke (2008) and Curi, Gitto and Mancuso (2011). This might be due to the fact that our sample of airports is slightly larger than the samples in previous studies, and our time span is much longer. On the basis of the results of our tests, we estimated our models under VRS. It should be noted that, as a check, we performed the same estimations under CRS; the sign and statistical significance of the parameters did not differ.

Table 5 presents the results of a series of regressions of the reciprocal of efficiency score, in the range from 1 to infinity. Including the variable for the percentage of low cost carriers reduces the sample size from 258 to 185 observations.

The effect of the presence of a high speed rail link in the region is always positive for the efficiency score (negative for its reciprocal). The coefficient tends to decrease after the inclusion of controls, but its sign remains constant and its significance is below 1% even in the most general specification (with low cost and year fixed effects added).

Table 6 presents an evaluation of the effect of the increase of 100, 200 and 500 km in the HSR network on airports where there is a station in the region. The evaluation uses the coefficient estimated in the most general specification. The coefficient representing the effect of low cost air carriers seems to be robust to the inclusion of covariates. Its negative sign suggests a positive effect on efficiency.

For the other control variables, again, strategic airports and, especially strategic international airports, seem to enjoy an efficiency advantage even after controlling for the presence of VRS in the computation of efficiency scores, while the geographical location of an airport seems to have no impact on efficiency once the effects of the other variables are controlled for.

3. Conclusion

This study provides for the first time the evaluation of the effect of HSR on the efficiency of the Italian airports' system. The development of HSR has received growing attention from governments and policy makers and has been considered as boosting countries' economic development and benefiting the environment. In this paper we examined the interaction of HSR with the existing infrastructure in the case of Italy, where investments in HSR have increased since the mid 2000s, in order to understand how the new infrastructure is affecting the existing one. Our results should help the planning of future transportation investments and developments.

In line with Barros and Dieke (2008) we also find that to be located in the northern part of the country, where infrastructure are more well developed than in the south, contribute to the efficiency improvements.

Policy makers can now use these results for improving the management of the Italian transport system. Our evaluation of the impact of HSR on the technical efficiency of the Italian airport system employed two stage estimation. We observed 31 Italian airports between 2003 and 2014, and found that the development of HSR has a positive impact on the technical efficiency of Italian airports. We conducted some robustness checks by controlling for the presence of low costs companies and international flights. Our results should help policy makers to improve the efficiency of regional travel.

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