Airport efficiency: a DEA two stage analysis of the Italian commercial airports

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Abstract
In this paper we use a two stage procedure, based on bias corrected DEA, to evaluate the impacts of regulatory reforms on technical efficiency of 28 Italian airports during the period 2000–2006. We employ two different DEA models: *physical* and *monetary*. The first relies on the aeronautical activities, the second concerns both aeronautical and non aeronautical business and allows us to evaluate the impact of commercial activities on overall airport efficiency. The main results are: i) mixed government-private ownerships with a private majority are more efficient than those with a government majority; ii) the liberalization of ground handling services has produced an increase of efficiency in airside and landside activities; iii) granting all services to airport management companies can be a source of inefficiency due to the lack of competition in the industry; iv) the introduction of dual-till increases overall technical efficiency.

Keywords: Data Envelopment Analysis (DEA), bootstrap, two stage estimation, airport efficiency.

1. Introduction

In the ranking of the "World's Top Tourism" destination by both international tourist arrivals and international tourism receipts, Italy holds respectively the fifth and the fourth position in 2007 (UNWTO, 2008). Between 2000 and 2006, the number of air passengers and cargo has been characterized by an average increase of, 5.0% and 3.3% per annum, respectively. In the same period low cost carriers have triggered the demand served by regional airports by a growth rate greater than 15.05% per annum. In Italy, as in most countries, the airport evolves to become a more sophisticated market entity that may be considered as a "multipoint" service-provider firm(Jarach, 2001).

Airside business is enlarged by increasing commercial activities, which involves not only air passengers and air transportation employees, but also local-community residents and industries. An efficient airport provides important economic catalysts that enable the local and regional economy to thrive and improve the quality of life in the region (Oum et al., 2008). Governments around the world have taken policy measures in order to improve the efficiency and the productivity of airport operations. In Italy government intervention started during the 90's and is still not completed. The reforms, which have completely reshaped the industry boundaries, concern the concession agreement, the privatization, the liberalization of the ground handling services, the development of a second hub and the introduction of a dual-till regulation scheme. Many scientific papers have been published on airport performances employing parametric and nonparametric methods (Gillen and Lall, 1997; Hooper and Hensher, 1997; Sarkis, 2000; Adler and Berechman, 2001; Martín and Román, 2001; Pels et al., 2001, 2003; Fernandes and Pacheco, 2003; Oum et al., 2003, 2004, 2006, 2008; Sarkis and Talluri, 2004; Yoshida and Fujimoto, 2004; Malighetti et al., 2007; Barros and Dieke 2007, 2008; Curi et al., 2010; Abrate and Erbetta, 2010). In recent years, the performance of the Italian airport industry has been analyzed by Malighetti et al. (2007), Barros and Dieke (2007, 2008), Curi et al. (2010) and Abrate and Erbetta (2010) amongst others. However, to our knowledge, there are no studies that assess through an econometric analysis the impacts of regulatory reforms on the performance of the Italian airport industry. Thus we apply a two-stage procedure based on a double bootstrap technique (Simar and Wilson, 2007) to a dataset composed of 28 Italian airports observed from 2000 to 2006; the main purpose of this paper is to measure the effects of regulatory changes on technical efficiency, whilst controlling for a set of independent variables. Moreover departing from previous studies, we disentangle the efficiency related to the airport operations from the efficiency related to the management of all the business activities. Results may contribute to improve the knowledge of the decision makers, both at regulatory and managerial level, on the evolution of the sector in Italy.

The paper is organized as follows: Section 2 presents the regulatory framework, Section 3 focuses on the methodology, Section 4 describes the dataset as well as the input and output variables used in the analysis. Results are discussed in Section 5, and some concluding remarks are made in Section 6.

2. Regulatory framework

In recent years, airports have been under growing pressure to be more financially self-sufficient and less reliant on government support (Carney and Mew, 2003). At a worldwide level, the key elements of the current discussion focus on the privatization of management companies, price regulation, and the increased competition among airports within the same country. As today, Italian airport companies manage the airports according to one of the three alternative types of concession agreement: "Total" (T), "Partial" (P) and "Precarious Partial" (PP).

The Total agreement allows the company to manage the activities in both airside and landside. The management company receives revenues from all the business and is in charge of the maintenance of all airport infrastructures. Through the P agreement, the management company is only responsible for the landside and its relative pertinence. The management company receives both passenger terminal charges and non-aeronautical revenues from commercial activities, including shopping concessions, car parking, etc. Ente Nazionale Aviazione Civile (Enac[1]) is responsible on behalf of the State for maintaining and developing airside. Finally the PP agreement restricts revenues for the airport management company to only commercial activities. T agreement allows a forty year concession while both P and PP limit the concession period to twenty years. By the 90's, several laws and administrative acts were introduced by the State with the aim of increasing competition and efficiency. The privatization process started in 1992 (laws n.1498/92 and n.1537/93), when airport authorities became stock companies. Nowadays, in most cases the airport management companies are characterized by a mixed government-private ownership with a local government majority. Moreover, with law n. 537/93 and ministerial decree n. 521/97, all airport management companies can apply to obtain a T concession. The business plans are evaluated by Enac, which after four years of trial, awarded the T concession. In 1998, the Italian government took

[1] Enac was established on 25th July 1997 by Legislative Decree no.250/97 as the National Authority committed to oversee the technical regulation, the surveillance and the control in the civil aviation field.

on a network configuration deploying two closely located hubs (Roma Fiumicino and Milano Malpensa). In 1999 the European directive on liberalization of ground handling services (EU 96/67), forced airport management companies to open the handling market to competition from 2001. However, Italian law protects handling workers and forces the new handling companies to hire workers from the incumbents (Cló, 2004). In 2001, the Italian Committee for the economic planning (CIPE-Comitato Interministeriale per la Programmazione Economica) has introduced a dual-till price cap (act n.86/2000). Tariffs are price capped on the airside, while on the landside the monopolistic rents are "skimmed" via specific royalties. At the end of 2005 the law n.248/2005 introduced a modified single till. The tariff is determined taking into consideration the operating and maintenance costs pertaining to aeronautical services, depreciation and returns on aeronautical assets and 50% of gross revenues generated from commercial activities (CERTeT, 2006). Moreover, due to this law, the airport management companies are in charge of the provision of all security services. The cost increase generated by the provision of security services has been balanced by a 75% reduction in the concession fee due from the airport management company to the State. Thus all the above factors, affecting airport physical and monetary flows (see Fig.1), can have an impact on airport efficiency and they will be investigated in the following sections.

Insert Figure 1 approximately here

3. Methodology

To analyze the effects of regulatory changes on the technical efficiency of Italian airports we employ a two-stage procedure. In the first stage, we calculate the technical efficiency from 2000 to 2006 for each airport. In the second stage, we run regressions to examine the effects of regulatory changes on the technical efficiency of airports, whilst controlling for a set of independent variables. In particular, in the first stage, we calculate the technical efficiency by DEA (Charnes et al., 1978). In the second stage, following the paper by Simar and Wilson (2007) we run truncated regressions to examine the effects of regulatory changes on the technical efficiency of airports, whilst controlling for a set of independent variables. We assume an output-orientated model as it ensures accounting the objective of exploiting the facilities to satisfy the steady growth demand in the aviation market (Martìn and Romàn, 2001). Moreover, we make use of standard assumptions about the production set (Simar and Wilson, 2000) to analyze airport efficiency in an inferential setting. In fact, the traditional DEA-estimator is biased in its construction and is affected by uncertainty due to sample variation (Simar and Wilson, 1998, 2000, 2007). To remove these drawbacks, we apply the procedure proposed by Simar and Wilson (1998) to derive the sampling distributions of the DEA-estimator. It is based on the bootstrap technique in a Monte Carlo setting. In order to facilitate the interpretation of the results in the next sections, it is useful to recall that in the output orientated DEA model an efficiency score $\hat{D}$ is calculated for each decision making unit (DMU), by solving the following linear program:

$$\hat{\theta}_{it} = \left[\hat{D}_{it}\right]^{-1} = \max_{\theta\lambda} \theta$$

$$\begin{aligned} s.t. \quad & \mathrm{x}_{it} \geq X_t\lambda \qquad i=1,2...,n; \qquad t=1,2...,T \qquad (1) \\ & \theta \mathrm{y}_{it} \leq Y_t\lambda \\ & \lambda \geq 0 \end{aligned}$$

Where $\hat{\theta}_{it}$ and $\hat{D}_{it}$ are the Farrell (1957) and Shepard's (1970) distance functions, respectively; *n* is the number of DMUs and *T* is the number of time periods; $\mathbf{Y}_t$ is a *sxn* matrix of *s* outputs, $\mathbf{X}_t$ is a *rxn* matrix of *r* inputs and $\boldsymbol{\lambda}$ represent a *nx1* vector of weights which allows to obtain a convex combination between inputs and outputs. The above specification is under constant returns to scale (CRS); for a specification under variable returns to scale (VRS) the additional constraint **1'λ=0** is added, where **1'** is a vector of ones. For an output-oriented model, $\hat{\theta}_{it}$ is an inefficiency measure and assumes always values equal to or greater than one. Consequently, $\hat{D}_{it}$ is an efficiency measure and it assumes values between zero and one. Airports with an efficiency score of unity are located on the frontier in the sense that their outputs cannot be further expanded without a corresponding increase in inputs. Further, the CRS model identifies the overall inefficiency whereas VRS model differentiates between (pure) technical efficiency and scale efficiency. The ratio between CRS score and VRS score provides a measurement of scale efficiency (Simar and Wilson, 2002).

However, relation (1) does not allow us to determine whether the efficiency values are real, or merely an artifact of the fact that we do not know the true production frontiers and must estimate them from a finite sample (Simar and Wilson, 2000). Thus, following the mentioned authors we employ a consistent bootstrap estimation procedure for correcting the efficiency scores. The idea underlying the bootstrap is to approximate the sampling distributions of θ, by simulating their data generating process (DGP). In other terms, given the estimates $\hat{\theta}_{it}$ of the unknown true values of θ_{it} we generate through the DGP process a series of pseudo datasets to obtain bootstrap estimate $\hat{\theta}^{*}_{it}$. If the bootstrap is consistent, then:

$$\left(\hat{\theta}_{it} - \theta_{it}\right)\Big| S \overset{approx}{\sim} \left(\hat{\theta}^{*}_{it} - \hat{\theta}_{it}\right)\Big| S^{*} \qquad t=1,2,\ldots, T \qquad (2)$$

Where, S and S^* denotes the observed and the bootstrap sample. To gain consistence on the empirical distribution of efficiency, we use a smooth bootstrap procedure (Simar and Wilson, 1998). Expression (2) implies that the relation between the original estimates $\hat{\theta}_{it}$ and the true values θ_{it} can be approximated by the relation between the bootstrapped estimates $\hat{\theta}^*_{it}$ and original estimates $\hat{\theta}_{it}$. At this point, the bias of efficiency scores is estimated by their bootstrap approximations $\hat{bias}_{S^*,t} = E_{S^*}(\hat{\theta}^*_{it}) - \hat{\theta}_{it}$; and bias-corrected estimates can be obtained as:

$$\tilde{\theta}_{it} = \hat{\theta}_{it} - \hat{bias}_{it} = 2\hat{\theta}_{it} - B^{-1}\sum_{b=1}^{B}\hat{\theta}^*_{it,b} \qquad t = 1,2,\ldots, T \qquad (3)$$

Where B is the number of the bootstrap replications. However, the bias correction introduces additional noise that increases the variance of the estimator. Thus, as rule of thumb, Efron and Tibshrani (1993) recommended not to correct for the bias unless $\left|\hat{\mathrm{b}}\mathrm{ias}_{\mathrm{it}}\right| > 4\ \hat{s}td(\hat{\theta}^*_{it})$. Kneip et al. (2008) provided the consistence of this bootstrap procedure. Furthermore, the above algorithm allows us to run a test on the global returns to scale supported by the technology (Simar and Wilson, 2002). The economic literature defines two types of returns to scale: local returns to scale and global returns to scale. While local returns to scale indicate the type of resizing of the unit in which immediate gains in productivity should be available, global returns to scale indicate the type of resizing in which the global maximum productivity can be achieved. In a convex technology the two type of measure are identical (Podinovski, 2004).

Now, according to Fig.1, we estimate the bias corrected efficiencies (3) for two complementary DEA models labeled, respectively, *physic (ph)* and the *monetary (mo)*. Through the *ph* model we mainly asses the efficiency of the management company in the airport operations (Sarkis, 2000) while with the *mo* one we consider the airport as a multipoint service-provider firm (Jarach, 2001). In the latter case, we analyze the airport management company in exploiting aeronautical and non-aeronautical business. In fact, the omission of some outputs such as commercial services is likely to bias efficiency results as it underestimates productivity of the airports with proactive managers who focus on exploiting the revenue generation opportunities from non-aviation business (Oum et al., 2003).

The econometric model in our two-stage analysis takes the form of a truncated regression model (Simar and Wilson, 2007):

$$\hat{\theta}_{it} = \mathbf{z}_{it}\boldsymbol{\beta} + \varepsilon_{it} \qquad i=1,2,\ldots, n;\ t=1,2,\ldots, T \qquad (4)$$

Where $\hat{\theta}_{it}$ are obtained by (1) and $\mathbf{z}_{it}$ is a set of explained variables for each unit *i* at time *t* and ε_{it} is $N(0,\sigma)$ with left-truncation at $\mathbf{1}-\mathbf{z}_{it}\boldsymbol{\beta}$. Separability between inputs and outputs and environmental variables is assumed. The regression parameters are estimated by truncated regression with a double bootstrap method to overcome the difficulties discussed by Simar and Wilson (2007). The algorithm is given in appendix A; it was developed using FEAR library (Wilson, 2007) for R software.

4. Sample of airports and variable construction

4.1 Input and output variables

We consider a balanced panel data of 28 Italian airports in the period between 2000 and 2006. Our sample includes the airports that represent different ownerships and operational characteristics and it covers, on average, 96%, 99% and 99% of total number of passengers, movements and cargos registered in Italy during 2000-2006. Data has been collected from: airport annual statistics (Enac, 2006), annual reports of airport management and handling companies and Italian National Institute of Statistic (ISTAT). Now, a management company can operate one or more airports and since it is not possible to obtain disaggregated economic data from the balance sheets as well as from Enac, we consider the management companies as DMUs. This means the aggregation of some physical variables concerning the airports managed by the same company. Moreover, in order to correctly assess technical efficiency in the *ph* model, as consequence of the liberalization of ground handling services in 2001, we integrate the data on the number of workers of the airport management company with those of the handling companies. The absence of such correction may reduce the goodness of the efficiency analysis in the *ph* model as can be deduced by looking at Fig.2.

Insert Figure 2 approximately here

In the *ph* model, we use three outputs: number of movements, number of passengers and amount of cargo. On input side, we consider the number of workers, runway area and airport area. As far as the *mo* model is concerned, the outputs are aeronautical and non-aeronautical revenues; as inputs, we use labor cost, capital invested and soft costs (Oum et al., 2004).

4.2 Airports characteristics

In order to examine the hypothesis that the efficiency is affected by environmental variables we consider the following elements:

Airport dimension: the size is an important factor in determining the operational performance of airports (Pels et al., 2003). Using classification of European Commission (EC, 2005), we identify four airport categories:

- large Community airports (lca), with more than 10 million passengers a year;
- national airports (naa), with an annual passenger volume of between 5 and 10 million;
- large regional airports (lra), with an annual passenger volume of between 1 and 5 million;
- small regional airports (sra) with an annual passenger volume of less than 1 million.

Demand for air transport: it is widely known that the Italian economy is affected by strong territorial disparities: GDP per capita in the South is around 60% of that in the Centre and North (Bronzini and Piselli, 2009). In order to take into account the economic impact of the area where the airport is located, we include the variable *lw*, which is obtained by dividing the value added per person relative to the airport area by the national value added per person. This variable has been introduced to measure the impact that economic development can lead to airport activities (Donzelli, 2010). Moreover, seasonality is considered to measure the difference in efficiency of airports with a strong influence of tourist seasonal movements (Malighetti et al., 2007). This variable is defined as follows: $s_t = y_t^{max} / y_t^{min}$; where y_t^{min} and y_t^{max} are respectively the minimum and the maximum number of monthly passengers in the year *t*. Finally, in order to take into account further macroeconomic shocks, a time variables *t* is introduced.

Regulatory changes: as noticed in Section 2, Italian airport industry has undergone several reforms. Airport ownership is measured by the dummy *kc*, which takes on the value *1* if the airport has a private majority ownership and *0* otherwise. The alternative concession agreements are identified through two dummy variables: *T* and *P*. *T* assigns value 1 to airports holding Total concession while P is equal to 1 for airport holding Partial concession. Airports in which operate more than one handling company[2] are identified by the dummy *hh*. Finally, the dummy *dt* takes into consideration the introduction of the dual-till regulation on airside activities in 2001.

Table 1 provides sample statistics for the variables and Table 2 completes the description of the characteristics of the Italian airports.

Insert Table 1 approximately here

Insert Table 2 approximately here

[2] We exclude handling services directly operated by airlines (self-handling).

5. Empirical results

5.1 Preliminary analysis

In DEA models, an excessive number of inputs and outputs, respecting the number observations, results in a large number of efficient units (Olesen and Petersen, 1996; Kneip et al., 1998; Adler and Golany, 2001). In our sample, the correlation matrix reveals the presence of high correlation among inputs and outputs (Table 3) and in this case, a suitable aggregation of variables is recommended. Now, following the procedure proposed by Daraio and Simar (2007), the aggregate input (output) variable, or factor, is obtained as a weighted sum of the original variables with weight represented by the values of the first eigenvalue of the input (output) matrix[3]. Table 4 reports the factors for each model with their relative inertia[4].

Insert Table 3 approximately here

Insert Table 4 approximately here

The percentage of inertia explained by the aggregate variables is very high; therefore, it is certainly appropriate to summarize the information of the full data matrix by these factors. The idea of analysing airport efficiency through the physical *(ph)* and the monetary *(mo)* model is *a posteriori* supported by the analysis of estimated distributions of technical efficiency. Indeed, Fig.3 highlights divergence on the shape of density as well as in their modes and modality; in which intuitively the levels of efficiency observed most frequently for the two models.

Insert Figure 3 approximately here

5.2 Efficiency and Technology assessment

The analysis of returns to scale of the technology, see Table 5, shows the existence of global constant returns to scale and global variable returns to scale for the *ph* and the *mo* model, respectively.

Insert Table 5 approximately here

The presence of global constant returns to scale for the *ph* model indicates that the Italian airports are not able to improve efficiency on airside activities by reducing or increasing the

[3] Mathematically the aggregate variable is obtained as follows: **A= Xa**, where **X** is the matrix of the input (output) variables and a is the first eigenvector of the matrix **XX'**.

[4] The inertia is computed by dividing the first eigenvalue by the sum of all eigenvalues of the matrix **XX'**. It measures the capacity of the aggregate variable to summarize the information contained in the original variables. Value close to 1 indicates an accurate representation.

scale of their operations. However, we cannot exclude the presence of local returns to scale since the assumption on convexity may be violated.

Turning our attention to the *mo* model, we assess the presence, at the 10% significance level, of constant returns to scale technologies in 2002, 2005 and 2006, and variable returns to scale for the remaining years. Thus, three years after the introduction of dual-till regulation in 2001, the average airport moves toward a CRS technology. In fact, under a dual-till scheme, non-aeronautical services are not regulated, hence there is some scope for prices to be inefficiently high, but the airport will have the incentive to produce these services efficiently, and to invest efficiently (Forsyth, 2002). Table 6 provides the bias corrected efficiency scores for the *ph* model.

Insert Table 6 approximately here

The twenty-three airport management companies have progressively reduced their efficiency in the airside activities: 16.0% in 2006 against 24.9% in 2000. The reduction of the inter-quartile range reveals the existence of a technological catch-up process. The best performers, that is the management company with an efficiency level greater than 0.339, are airports with a number of passenger movements greater than one million, with the only exception of Treviso(TSF). Cagliari(CAG), located in Sardinia, is the airport that achieved , on average, the best input/output configuration. Cagliari (CAG) has been able to support the expansion of the terminal area, begun in 2000 and terminated in 2003, by increasing the traffic. In the first quartile we found airports located, with the exclusion of Trieste(TRS), in the center and south of the country and close to tourist locations. They are characterized by low traffic volume -Pescara(PSA), Trieste(TRS) and Puglia airports- and/or they face high seasonality in the traffic flows - Alghero(AHO) and Rimini(RMI)-. All the remaining airports show an average level of efficiency between 0.147 and 0.339.

Noticeable is the decline in technical efficiency of Rome's airport system, which can be explained by three factors: the opening of the second national hub of Malpensa(MPX), the impressive growth in the number of passengers of Ciampino(CIA) (+717%), generated by the low cost carrier Ryanair, and the building of a new runway in Fiumicino(FCO).

Table 7 shows the bias efficiency scores for the *mo* model and the analysis of the returns to scale.

Insert Table 7 approximately here

The higher average value of the technical efficiency and the smaller inter-quartile ranges suggest that airport management companies are closer to the frontier under the *ph* model than under the *mo* one. Now, in the last quarter of the distribution of the *mo* model (see Table 7), there are six airports: three show the persistence of decreasing returns to scale - Napoli (NAP), Pisa (PSA) and Venezia(VNA) - two of scale efficiency - Torino(TRN) and Olbia(OLB) - and one by scale efficiency and increasing returns to scale: Ancona(AOI). However looking at the scale index we can conclude that most of inefficiency relies on technical factors. About the regional airports of Torino (TRN) and Olbia (OLB), investment in airport infrastructures has led to significant increases, driven by low cost carriers, in the number of passengers. Olbia (OLB) is located in Costa Smeralda in the north-west of Sardegna. It is an example of a multipoint service-provider airport, which compensates for the poor efficiency value obtained in the core activities, due mainly to the high seasonality of its traffic, with an efficient management of the commercial ones. Moreover, it has been granted by the T concession in 2004. Napoli(NAP) and Venezia(VNA) hold a T concession and have majority private ownership while Pisa(PSA) is granted by a P concession. Ancona(AOI), a military airport open to civil traffic, is the only one that should slightly increase the output. We will further investigate these preliminary evidences in the second stage of the analysis. Finally, the first quartile is characterized by DMUs with efficiency less than 0.735: Alghero(AHO), Cagliari(CAG); Genova(GOA), Rimini(RMI), Trieste(TRS) and Puglia regional airports. The negative result obtained by Genova(GOA), which holds a T concession since 1954, can be ascribed to some contextual factors: lack of adequate connections to the city and the presence of five airports, with better connections in the range of 130 km. For the remaining airports, as we will analyze better below, the characteristics of the demand, low and with high seasonality, can be advocated to explain the low level of technical efficiencies. The last group includes the two large Community airport systems of Milano and Roma, as well as nine regional airports. The airport of Pescara(PSR) should increase its dimension in order to fully benefit from the increase of business generated by Ryanair. Similarly, the analysis of returns to scale suggests that the airports of Bergamo(BGY), Bologna(BLQ), Catania(CAT) and Verona(VRN) are too large in dimension.

4.3. Second-stage results

Second-stage results from the double bootstrap estimation are presented in Table 8. The dependent variable $\hat{\theta}$ is an inefficiency measure; therefore, the parameters with negative signs indicate sources of efficiency and vice versa.

Insert Table 8 approximately here

In analyzing the results of the two stage analysis some attention has to be taken into consideration when dummy variables are examined. In fact, if a dummy is not significant, it still might be fairly substantial from an economic point of view, but might not be empirically identified due to the low power of the test on coefficients of dummy variables (Zelenyuk, 2009). The implication is that, the corresponding policy conclusions are difficult to draw when the dummy variables in a two-stage analysis are not statistically significant. Taking into consideration the above observation we notice that mixed government-private ownership with a private majority contributes to the improved technical efficiency in both models. The results confirm the evidence by Oum et al. (2008) which suggests that countries considering the privatization of airports should transfer majority shares to the private sector. Thus our results, according to the agency theory and the strategic management literature, support the common-sense view that government-owned firms are less productively efficient than their private sector counterparts. Liberalization of ground handling services has lead to significant technical efficiency gains in both models. As far as the role played by the concession agreements the two stage analysis seems to suggest that as soon as the concession grant moves from PP to T, the level of inefficiency increases. However, from an economic point of view, we can only conclude that the T concession has a negative impact on technical efficiency related to airside and landside business. The presence of X-inefficiencies (Leibenstein, 1966), due to the monopolistic nature of non airside activities, can be advocated to explain such empirical evidence. However, in the airside activities of the Italian airport industry the level of competition appears low. Even where competition can exist thanks to the proximity of airports, this is in fact prevented by the ownership structure of these airports' management companies. This occurs in the airports of Puglia, Roma, Milano and Bergamo (see Table 1). The introduction of the dual-till regulation generates a positive significant impact on the technical efficiency of the monetary model and a negative, not significant, impact on the physical one. Thus even if this tariff scheme leads the airport to inefficiently increase prices of non-regulated non-aeronautical services, it is able to generate incentives to produce these services efficiently (Forsyth, 2002). However, the empirical evidence from the *ph* model, does not allow us to conclude if the possible (excess) profits earned by airports from non-aeronautical services has been utilized to improve airside operations.

The positive and significant coefficient of the dummy seasonality implies a negative impact of seasonal demand peak on the technical efficiency of airside operations. In fact, fluctuations in demand for airport services and investment indivisibilities leads inevitably to excess capacity with important repercussions for the airport efficiency (Walters, 1978). The negative and significant value of *lca* dummy suggests that the airport systems of Milano and Roma which include the two hubs of Malpensa(MPX) and Fiumicino(FCO) reach the highest technical efficiency improvement. This finding confirms. The widespread conclusion in writings on the subject that shows how hubs possess size and location advantages. For the remaining airports, we can only conclude that small regional airports should increase the number of passengers to gain operational efficiency. Thus the State should evaluate the possibility of closing some airports, distributing the air traffic to some other close airports (for example between Ancona(AOI) and Pescara(PSA) or among airports of Puglia). Unfortunately, our data does not allow us to draw any economic implications on the effect of airport dimension on the management of both airside and landside activities. Finally, a positive and statistical significant relationship between the efficiency score and per-capita GDP is found. Thus, a part of the difference between efficiencies of airports located in the North and those located in the South of Italy lies in the economic gap existing between the two geographic areas.

6. Conclusion

In this paper we use the Simar–Wilson's two-stage procedure to analyze the efficiency of 28 Italian airports from 2000 to 2006. Over the analyzed time period the Italian airport industry has experienced an important transformation concerning the change of the concession agreement, the privatization, the liberalization of ground handling services, the dual-till regulation and the development of a second national hub. In order to assess the impacts generated by the reform of the industry on technical efficiency, we develop two DEA models. The first, named *physical*, analyzes the technical efficiency of airport operations; while the second, named monetary, measures technical efficiency related to aeronautical and non-aeronautical activities. This research strategy has been supported, *a posteriori*, by the empirical analysis. In other terms, this paper highlights that efficient management of non-aeronautical business appears weakly related, in terms of technical efficiency, to the one connected to the traditional aeronautical business. Technology assessment reveals the presence of constant returns to scale technologies in the airport activities and both constant and variable returns to scale in the management of all business activities.

The two stage analysis shed some light on the impact generated by the regulatory reform on the Italian airport industry. In particular, we found that airport management companies with a private majority reach a higher level of technical efficiency than those with a government majority. A positive impact, in terms of technical efficiency gain, has been generated by the liberalization of ground handling services. The analysis suggests that the reduction of government control generated by a T concession causes an increase of the technical inefficiency in the provision of landside and airside services. Hence the lack of competition, enforced by the capital structure of close airports, increases the negative effect generated by the presence of X-inefficiencies on the management conduct. The data also suggests that the dual-till regulation increases overall technical efficiency. Unfortunately no empirical evidence can be drawn on the impact of the tariff scheme on airside activities. Another remarkable aspect concerns the possibility of the State gaining technical efficiency by reallocating traffic among close small regional airports. Moreover, seasonality creates difficulties for the regional airports, to obtain an optimal production scale. Finally, the analysis confirms the positive impact that the economic development produces on airport efficiency.

Appendix A: Simar and Wilson (2007) algorithm #2.

1) Compute $\hat{\theta}$ from relation (1) for each airports *i (i=1,2,…n)* at time *t (t=1,2,…T)*[5].
2) DMUs with $\hat{\theta} > 1$ are employed to estimate, by maximum likelihood, the parameters, $\hat{\boldsymbol{\beta}}$ and the standard error $\hat{\sigma}_{\varepsilon}$.
3) For each airport and for each bootstrap replication *b (b=1,2,…, B_1)* the following steps are executed:
   a) drawn the error component ε_b from a $N(0,\hat{\sigma})$ distribution with left truncation at $1-\mathbf{z}\hat{\boldsymbol{\beta}}_b$;
   b) compute the estimate $\hat{\theta}^*_b = \mathbf{z}_b\hat{\boldsymbol{\beta}}_b + \varepsilon_b$;
   c) compute the pseudo data set $(x^{\circ}_b, y^{\circ}_b)$, where $\mathbf{x}^{\circ}_b = \mathbf{x}$ and $y^{\circ}_b = \frac{\hat{\theta}_b}{\hat{\theta}^*_b} y$;
   d) obtain new DEA estimate $\widehat{\theta}^*_{\mathbf{b}}$ using $(x^{\circ}_b, y^{\circ}_b)$ as reference set.
4) By the bootstrap replications compute the bias corrected estimates $\tilde{\theta}$.
5) Use maximum likelihood to estimate the parameters $\tilde{\boldsymbol{\beta}}$ and the variance $\tilde{\sigma}$ of truncated regression of $\tilde{\theta}$ on $\mathbf{z}$.
6) To derive confidence intervals and significance levels for the regression parameters, a new loop is repeated B_2 times *(b'=1,2,…, B_2)*:
   a) drawn $\varepsilon_{b'}$ from a $N(0,\tilde{\sigma})$ distribution with left truncated at $1-\mathbf{z}\tilde{\boldsymbol{\beta}}_{b'}$;

[5] We supress the pedex to semplify the notation.

b) compute $\tilde{\theta}^{**}_{b'} = \mathbf{z}_{b'}\tilde{\boldsymbol{\beta}}_{b'} + \varepsilon_{b'}$;

c) use maximum likelihood to estimate the parameters $\tilde{\boldsymbol{\beta}}^{*}_{b'}$ and the variance $\tilde{\sigma}^{*}_{b'}$ of truncated regression of $\tilde{\theta}^{**}$ on $\mathbf{z}$.

7) By the bootstrap sample ($\tilde{\boldsymbol{\beta}}^{*}_{b'}, \tilde{\sigma}^{*}_{b'}$) compute the confidence intervals for $\tilde{\boldsymbol{\beta}}$ and $\tilde{\sigma}$ by selecting the appropriate percentiles.

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Figures. Airport efficiency: a DEA two stage analysis of the Italian airports.

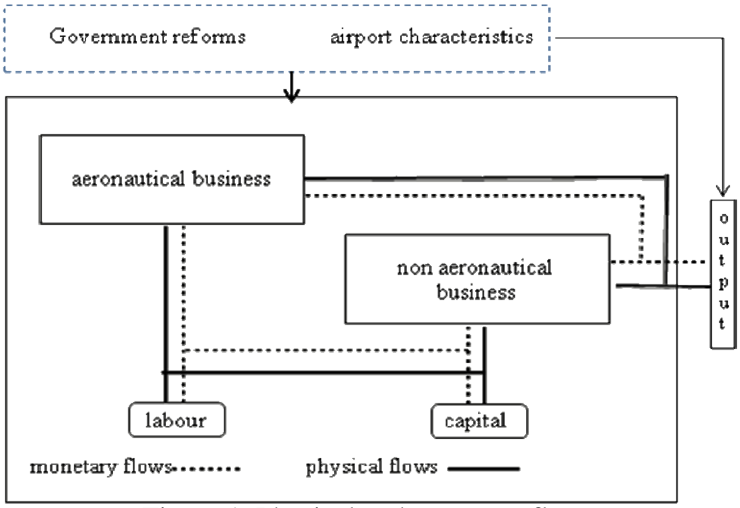

Figure 1. Physical and monetary flows.

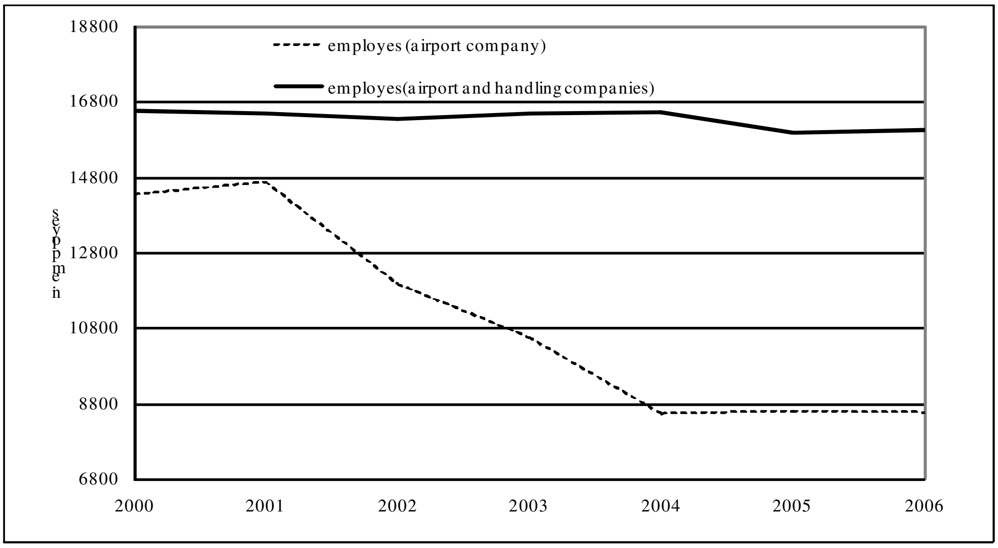

Figure 2. Evolution of workers in the Italian ground handling services.

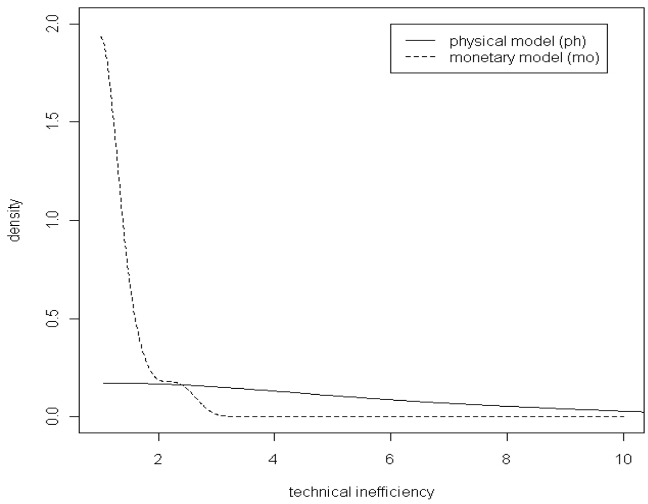

Figure 3. Estimated density of efficiency distribution for physical and monetary model.

Tables. Airport efficiency: a DEA two stage analysis of the Italian airports.

Table 1. Characteristics of Italian airports.

Airport (IATA CODE)	Ownership (*o*) 1=private; 0=public.	Types of concession agreement (*ca*) (year of agreement)	Number of handlers (*hs*) 1 = # handlers >1; 0 = # handlers = 1	Airport category
Alghero (AHO)	0	PP	0	sra, lra
Ancona (AOI)	0	PP	0	sra
Bari, Brindisi, Foggia, Taranto (BRI, BDS, FOG, TAR)	0	T (2002)	0	lra
Bergamo (BGY)[6]	0	T (1975)	1	lra, naa
Bologna (BLQ)	0	T (2004)	1	lra
Cagliari (CAG)	0	P	1	lra
Catania (CTA)	1	P	1	lra, naa
Firenze (FLR)	1	T (2001)	0	lra
Genova (GOA)	0	T (1954)	1	lra
Lamezia (SUF)	0	PP	1	sra, lra
Milano Linate, Malpensa (LIN, MXP)	0	T (1962)	1	lca
Napoli (NAP)	1	T (2002)	1	lra
Olbia (OLB)	1	T (2004)	0	lra
Palermo (PMO)	0	P	1	lra
Pescara (PSR)	0	PP	0	sra
Pisa (PSA)	0	P	1	lra
Rimini (RMI)	0	0	0	sra
Roma Ciampino, Fiumicino (CIA, FCO)	1	T (1973)	1	lca
Torino (TRN)	0	T (1965)	1	lra
Treviso (TSF)	0	P	0	sra
Trieste (TRS)	0	P	0	sra
Venezia (VCE)	1	T (1986)	1	lra, naa
Verona (VRN)	0	P	0	lra

Types of concession agreement: Total (T), Partial (P), Precarious Partial (PP). Airport categories: large Community airport (lca), national airport (naa), large regional airport (lra), small regional airport (sra).

[6] Airport management company of Milano holds 49% of airport management company of Bergamo.

Table 2. Outputs and inputs: descriptive statistics

models	variables	definition	min	max	mean	variation coef.
physical						
	outputs					
	number of movements	total number of plans that lands and takes-off from the airport (unit)	5076	379542	60088.7	1.48
	number of passengers	number of passenger who arrive at or depart from the airport (unit)	114024	35121826	4402276.7	1.73
	amount of cargo	amount of cargo (ton)	489	446596	37474.6	2.29
	inputs					
	labour	number of equivalent employees (unit)	23.06	6835.84	701.18	2.17
	runway area	total runways area (m^2)	49500	2763600	241066.9	1.41
	airport area	airport area (ha)	55	1825	376.4	1.16
monetary						
	outputs					
	aeronautical revenues	Revenues derived from aeronautical business (millions of euros)	1544	394360	41542.0	1.78
	non aeronautical revenues	Revenues derived from non-aeronautical business (millions of euros)	297.35	245767	24622.1	2.30
	inputs					
	labour cost	labour cost (millions of euros)	969.1	263458	19888.3	1.99
	capital invested	book value of fixed asset (millions of euros)	1481.1	2375682.2	171888.6	2.89
	soft cost	operation cost excluding labour and capital costs (millions of euros)	966.8	186562.8	23627.0	1.64
	environmental variables					
	seasonality *(s)*	ratio of the maximum to the minimum number of passengers per month	1.24	11.83	2.639	0.68
	wealth *(we)*	value added per person relative to the airport area divided by the national value added per person	62.91	159.40	101.70	0.26

Table 3. Correlations between variables.

models							
physical (ph)							
		labour	airport area	runway area	passengers	cargos	movements
	labour	1.000					
	airport area	0.933	1.000				
	runway area	0.504	0.518	1.000			
	passenger	0.967	0.937	0.524	1.000		
	cargo	0.927	0.846	0.403	0.886	1.000	
	movement	0.977	0.938	0.522	0.995	0.904	1.000

monetary (mo)							
		labour cost	soft cost	capital invested	aeronautical revenues	non aeronau-tical revenues	
	labour cost	1.000					
	soft cost	0.875	1.000				
	capital invested	0.758	0.941	1.000			
	aeronautical revenues	0.966	0.945	0.856	1.000		
	non aeronautical revenues	0.878	0.977	0.959	0.951	1.000	

Table 4. Factors and inertia.

model	factors	original variables	inertia
physical (ph)			
outputs			
	Po_1	number of movements, of passengers and amount of cargo	0.952
inputs			
	Pi_1	labour and airport area	0965
	Pi_2	runway area	
monetary (mo)y			
outputs			
	Mo_1	aeronautical revenues and non aeronautical revenues	0.979
inputs			
	Mi_1	capital invested and soft cost	
	Mi_1	labour cost	0.972

Table 5. Returns to scale: p-values. 5000 bootstrap replications.

	years						
models	2000	2001	2002	2003	2004	2005	2006
physical *(ph)*							
H_0 CRS; H_1: otherwise	0.947	0.952	0.947	0.913	0.942	0.937	0.914
H_0 NIRS; H_1: VRS							
monetary *(mo)*							
H_0 CRS; H_1: otherwise	0.025	0.060	0.116	0.061	0.034	0.102	0.320
H_0 NIRS; H_1: VRS	0.006	0.011	0.031	0.022	0.004	0.038	0.637

CSR=constant returns to scale; VRS=variable returns to scale; NIRS = non increasing returns to scale.

Table 6. Bias corrected efficiency scores for the physical *(ph)* model. 5000 bootstrap replications.

	technical efficiency scores							
airports(IATA CODE)	2000	2001	2002	2003	2004	2005	2006	geometric mean
Alghero(AHO)	0.111	0.121	0.104	0.101	0.106	0.088	0.073	0.100
Ancona(AOI)	0.196	0.227	0.210	0.205	0.202	0.151	0.122	0.184
Bari, Brindisi, Foggia and Taranto(BDS BRI FOG TAR)	0.138	0.146	0.113	0.124	0.116	0.084	0.079	0.112
Bergamo(BGY)	0.609	0.590	0.496	0.448	0.487	0.388	0.399	0.482
Bologna(BLQ)	0.531	0.508	0.417	0.313	0.313	0.336	0.319	0.381
Cagliari(CAG)	0.788	0.803	0.786	0.695	0.743	0.651	0.590	0.718
Catania(CTA)	0.418	0.415	0.334	0.320	0.302	0.245	0.239	0.318
Firenze(FLR)	0.418	0.401	0.308	0.252	0.261	0.226	0.177	0.280
Genova(GOA)	0.216	0.235	0.203	0.221	0.206	0.159	0.147	0.196
Lamezia(SUF)	0.082	0.117	0.109	0.106	0.122	0.078	0.066	0.095
Milano Linate and Malpensa(LIN MXP)	0.562	0.449	0.541	0.598	0.583	0.496	0.516	0.533
Napoli(NAP)	0.466	0.542	0.527	0.457	0.325	0.225	0.154	0.353
Olbia(OLB)	0.283	0.305	0.265	0.186	0.147	0.120	0.112	0.188
Palermo(PMO)	0.332	0.355	0.301	0.290	0.288	0.223	0.233	0.285
Pescara(PSR)	0.132	0.134	0.145	0.132	0.132	0.113	0.112	0.128
Pisa(PSA)	0.147	0.189	0.163	0.180	0.181	0.149	0.150	0.165
Rimini(RMI)	0.058	0.070	0.054	0.047	0.061	0.036	0.025	0.048
Roma Ciampino and Fiumicino(CIA FCO)	0.433	0.397	0.358	0.306	0.311	0.260	0.253	0.325
Torino(TRN)	0.255	0.270	0.166	0.205	0.228	0.176	0.153	0.203
Treviso(TSF)	0.304	0.413	0.403	0.418	0.489	0.438	0.398	0.405
Trieste(TRS)	0.110	0.128	0.115	0.102	0.103	0.081	0.076	0.101
Venezia(VCE)	0.196	0.228	0.217	0.220	0.200	0.198	0.194	0.207
Verona(VRN)	0.265	0.262	0.223	0.185	0.153	0.112	0.117	0.234
geometric mean (bias uncorrected)	0.249 (0.353)	0.268 (0.378)	0.235 (0.350)	0.221 (0.333)	0.220 (0.329)	0.176 (0.293)	0.160 (0.278)	0.218 (0.327)
first quartile	0.143	0.168	0.154	0.156	0.140	0.113	0.112	0.147
third quartile	0.426	0.414	0.381	0.317	0.312	0.253	0.246	0.339
interquartile range	0.283	0.247	0.227	0.161	0.173	0.140	0.134	0.193

Table 7. Bias corrected efficiency scores for the monetary *(mo)* model. 5000 bootstrap replications.

	pure technical efficiency scores (returns to scale)								scale efficiency	
airports(IATA CODE)	2000	2001	2002	2003	2004	2005	2006	geometric mean	geometric mean	returns to scale mode
Alghero(AHO)	0.816(i)	0.739(i)	0.545(i)	0.388(i)	0.579(i)	0.460(i)	0.362(d)	0.533	0.815	i
Ancona(AOI)	0.793(s)	0.885(s)	0.838(i)	0.778(i)	0.889(i)	0.787(s)	0.858(i)	0.831	0.990	i,s
Bari, Brindisi, Foggia, Taranto (BRI, BDS, FOG, TAR)	0.552(d)	0.444(d)	0.574(d)	0.674(i)	0.488(i)	0.454(d)	0.390(i)	0.503	0.997	d
Bergamo(BGY)	0.742(d)	0.675(d)	0.614(d)	0.705(d)	0.871(d)	0.946(d)	0.844(d)	0.763	0.869	d
Bologna(BLQ)	0.897(d)	0.938(d)	0.821(d)	0.771(d)	0.682(d)	0.724(d)	0.685(d)	0.783	0.877	d
Cagliari(CAG)	0.449(d)	0.568(i)	0.855(i)	0.855(s)	0.658(i)	0.492(d)	0.525(i)	0.611	0.949	i
Catania(CTA)	0.737(d)	0.841(d)	0.778(d)	0.936(d)	0.796(d)	0.786(d)	0.603(d)	0.776	0.874	d
Firenze(FLR)	0.817(d)	0.807(d)	0.747(d)	0.746(d)	0.768(d)	0.938(d)	0.655(d)	0.779	0.973	d
Genova(GOA)	0.540(d)	0.434(d)	0.478(s)	0.554(d)	0.777(i)	0.892(s)	0.801(s)	0.618	0.984	d,s
Lamezia(SUF)	0.749(i)	0.921(i)	0.768(s)	0.757(s)	0.808(s)	0.835(i)	0.705(i)	0.789	1.012	i,s
Milano Linate and Malpensa(LIN MXP)	0.768(d)	0.772(d)	0.758(d)	0.773(d)	0.812(d)	0.844(d)	0.698(d)	0.774	0.939	d
Napoli(NAP)	0.907(d)	0.904(s)	0.676(d)	0.818(d)	0.860(d)	0.954(d)	0.783(d)	0.838	0.943	d
Olbia(OLB)	0.856(s)	0.870(s)	0.872(s)	0.767(d)	0.923(s)	0.943(s)	0.913(d)	0.876	0.991	s
Palermo(PMO)	0.886(s)	0.920(d)	0.894(d)	0.528(d)	0.625(d)	0.804(d)	0.791(d)	0.765	0.911	d
Pescara(PSR)	0.772(i)	0.775(i)	0.755(i)	0.733(i)	0.796(i)	0.784(i)	0.609(s)	0.744	0.635	i
Pisa(PSA)	0.829(d)	0.899(d)	0.829(d)	0.848(d)	0.846(d)	0.940(d)	0.863(d)	0.864	0.910	d
Rimini(RMI)	0.657(i)	0.799(i)	0.758(i)	0.734(i)	0.812(i)	0.781(i)	0.399(d)	0.689	0.781	i
Roma Ciampino and Fiumicino(CIA FCO)	0.794(d)	0.772(d)	0.753(s)	0.793(d)	0.833(d)	0.850(d)	0.714(s)	0.786	0.967	d
Torino(TRN)	0.831(d)	0.893(d)	0.892(s)	0.836(s)	0.854(s)	0.953(i)	0.872(s)	0.875	0.999	s
Treviso(TSF)	0.704(i)	0.882(i)	0.788(i)	0.806(i)	0.871(i)	0.847(i)	0.640(i)	0.787	0.904	i
Trieste(TRS)	0.871(i)	0.776(i)	0.618(i)	0.617(i)	0.838(i)	0.900(i)	0.548(d)	0.726	0.886	i
Venezia(VCE)	0.796(d)	0.895(d)	0.789(d)	0.869(d)	0.908(d)	0.911(s)	0.826(d)	0.855	0.929	d
Verona(VRN)	0.728(d)	0.760(d)	0.712(d)	0.776(d)	0.902(d)	0.823(d)	0.779(d)	0.781	0.867	d
geometric mean (bias uncorrected)	0.750 (0.849)	0.775 (0.861)	0.735 (0.844)	0.730 (0.836)	0.782 (0.864)	0.794 (0.873)	0.669 (0.780)	0.747 (0.843)	0.909 (0.876)	
first quartile	0.733	0.766	0.694	0.719	0.773	0.785	0.606	0.735	0.876	
third quartile	0.830	0.894	0.825	0.812	0.866	0.925	0.813	0.810	0.979	
interquartile range	0.098	0.128	0.131	0.093	0.093	0.140	0.208	0.076	0.103	
increasing return (i)	6	7	7	7	9	7	5			
decreasing return (d)	14	13	11	13	11	12	14			
scale efficiency (s)	3	3	5	3	3	4	4			

Table 8. Determinants of technical inefficiency

	physical model *(ph)*	monetary mode *(mo)*
coefficients	estimate	estimate
intercept	7.549***	2.118***
total concession *(T)*	2.216	1.120**
partial concession *(P)*	1.466	0.265
ownership *(o)*	-5.417***	-1.236**
handling *(hs)*	-5.177***	-0.728**
seasonality *(s)*	0.986***	-0.038
wealth *(we)*	-0.072***	-0.018**
time	1.067***	0.146**
large Community airports *(lca)*	-16.527**	-0.798
national airports *(naa)*	-3.154	0.173
large regional airports *(lra)*	-6.554***	0.025
dual-till regulation	0.856	-0.838**
sigma	3.457***	0.541***

Statistical significance: ***statistically significant at 1% level, **statistically significant at 5% level, *statistically significant at 10% level according to the bootstrap confidence intervals. B1=1000, B2=2000 bootstrap replications.