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Key Words: efficiency, airports, Argentina

Abstract:
The main objectives of this paper are to measure the relative efficiency of Argentinean airports, and to infer possible regulatory consequences of the results. We pay attention to regional differences that could help the regulator in its task. At the same time, we try to determine which "environmental" variables (in the sense of particular conditions which are specific to different sets of airports) affect the relative efficiency of different airports. Since 1997, most of the airports were privatized, by means of concessions contracts.
Of the DEA analysis we derive two broad conclusions. Firstly, significant differences in efficiency are prevalent in Argentinean airports. Secondly, best-practice calculations indicate that much of the Argentinean airports operate at a high level of efficiency during the period.
Therefore, the overall conclusion is that Argentinean airports are mixed managed during the period as far as technical efficiency is concerned. Moreover, dimension makes a difference and therefore, some airports have decreasing returns to scale, while others have increasing returns to scale.

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1. Introduction

The main objectives of this paper are to measure the relative efficiency of Argentinean airports, and to infer possible regulatory consequences of the results. We pay attention to regional differences that could help the regulator in its task. At the same time, we try to determine which “environmental” variables (in the sense of particular conditions which are specific to different sets of airports) affect the relative efficiency of different airports.

Until 1997, the majority of the Argentinean airports were under direct administration, regulation and control of the local Air Force (Fuerza Aérea Argentina, FAA). Some provincial and municipal governments also had control over regional airports. Since 1997, most of the airports were privatized, by means of concessions contracts.

There are airports with different characteristics (international, domestic, touristy destinations, province capital, etcetera), which explain part or all of its traffic. Two thirds of the flights are concentrated in the two airports of the capital city of Buenos Aires, namely Ezeiza-Ministro Pistarini (international) and Aeroparque Jorge Newbery (domestic).

In Argentina, the domestic flight passengers increased markedly during the 1990s. In eight years the quantity of passengers rises in 138%, from three to seven million per annum between 1991 and 1999. Until 1990, the domestic flight services were provided mainly by two state owned firms (Aerolíneas Argentinas and Austral), both privatized in the 1990s. Nowadays, they are operating with an increasing role of the state in its ownership and control. They had 62% and 30.7% of the market share in 1991, respectively, and the remaining was provided by LADE (3.9%) and others (2.7%). LADE is a state owned enterprise, related to the FAA, which covers distant and non-profitable routes mainly in the Patagonia (South). In 1992 the Government opened the air transport of cargo, passengers and mail to the competition, favoring the entrance of new providers, stimulating the competition and freeing the price and tariff determination. For 1993/1994 new entrants started to enter to the market, and the supply of seats and flights increased (Briggs and Petrecolla, 2001).

The process of privatization of the airports started with the issuing of the Decree 375/97, amended by the Decree 500/97. The objective of the move was to increase investment in the sector, to introduce more competition and to address the coverage of an increased demand. The national system of airports included 58 airports, of which 36 were conceded for thirty years (with a ten year possible extension) to three consortiums[4] and the remaining airports continued under control of the Air Force, as well as some provincial or municipal governments. The greater concession pooled eight profitable airports with other twenty-five with the objective of improving the infrastructure of all of them and using cross subsidies[5].

The Decree 375/97 also created a regulator for the national system of airports, the ORSNA (“Organismo Regulador del Sistema Nacional de Aeropuertos”), in charge of the control, supervision and regulation of the airport activities. To read more details about the privatization process and its scope, see Lipovich (2008) and Petrecolla and Briggs (2001).

The openness to the competition in the markets of air shipped cargo, passengers and mail, increased supply of services and lower fares. But the increase of the traffic was stopped

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[4] Aeropuertos Argentina 2000 (33, sparse in the whole country), London Supply SA (2 in the southern Patagonia), and Aeropuertos del Neuquén SA (1 airport in the city of Neuquén).

[5] The consortium “Aeropuertos Argentina 2000” (AA2000) was awarded with the concession in February 1998. Originally was constituted by Corporación America Sudamericana CAS (35%), Ogden Corporation (in charge of the ground handling of the baggage, 28%), Società Per Azioni Esercizi Aeroportuali (SEA, operator of the Milan airport, 28%), Simest Spa Italy (8%) and Riva Construcciones (1%). In May 1998, AA2000 started its activity in the airports of Ezeiza, Aeroparque Jorge Newbery and Córdoba. In the following years, the rest of the airports awarded by the concession were gradually transferred to AA2000. The property of the shares is currently 80% in hands of CAS and 20% in hands of the National State.

by a macroeconomic downturn. A recession started at the end of 1998, and from 2001 to 2003 the economy underwent a dramatic crisis. Since January to July 2002, the local currency lost 75% of its value. During 2002, local GDP fell by an 11% fall of GDP and unemployment rate went to 24%. After almost eleven years of currency board (that pegged the parity between Peso and Dollar), the devaluation was followed by a generalized default on financial contracts, both domestically and at the international level. Local banking system collapses (Chisari and Ferro, 2005). The macroeconomic crisis in 2002, after the devaluation of the local currency, halved the air traffic and various airlines went bankrupt. But the devaluation also brought foreign tourism[6], the air traffic experienced a recovery, and the supply of services started to grow. While in 2005 there were only two airlines operating internal traffic, Aerolíneas Argentinas and Austral (in hands of the same group), constraints to foreign carriers were lift, and LAN Chile entered to the market with a local subsidiary, and some provincial little enterprises surged to serve particular routes. The concession contract was renegotiated in the period 2001-2006, easing the original investment commitment. The new contract set the basis of the contractual relationship for the last 22 years of the concession. Originally, the canon was fixed, and after the renegotiation it represents 15% of the annual revenue (San Martino, 2009).

The Decree 375/97 entitles ORSNA with the task of regulating the tariffs on services, aeronautics and non-aeronautics, each one with different treatment (Sesé and Gallacher, 2006). Aeronautic fares are the duties for airport usage and navigation, also customs and migration services, which under the contract are regulated. For instance, there are fares for landing, for parking, for the use of the air station, for security, for migration, for the usage of telescopic gangways, for flight protection in route, and for supporting landing operation. The non-aeronautic tariffs include a heterogeneous set of services, like catering for the aircrafts, duty-free shops, and fiscal stores. It is worth noting than the tariff regulation used is the single till approach[7] of the price cap. This system allows that non-aeronautic services (with no direct regulation) subsidize the aeronautic services.

The aeronautic fares, set by the Resolution 53/98, amended by the Decree 698/01, were established initially as price caps, adjusted every five years and corrected following the formula PPI[8] –X. The adjustment of the X-factor was done over the weighted average of certain variables: traffic increase, efficiency improvements, level of quality of service, projected investment and rate of return projection.

Analyzing aeronautic tariff regulation in Latin American countries, only five countries (Argentina, Brazil, Peru, Colombia, and Bolivia) had an independent regulator. Most of them regulate by means of price cap (both, single till or dual till). Only Peru applies another regulatory scheme, based on costs.

In a more global context, the aeronautic market is regulated by several mechanisms. First, by price cap: United Kingdom, and some cases in Continental Europe, like Hamburg airport, which is regulated by a dual till approach (Gillen and Niemeier, 2006). Second, by Rate of Return Regulation (ROR), which pursues a fair retribution of the capital basis (United

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[6] From 2000 to 2007 foreign tourism of Argentina in relation to other Latin American markets increased from 19% of the market share, to 23%.

[7] There are two approaches to price cap in the airport industry: *single till regulation* and *dual till regulation*. The *dual till regulation* split tariffs in two parts (aeronautic and non aeronautic services) to make adjustments. For more details, see Gillen and Morrison (2001), or Gillen (2008).

[8] Productor Price Index, estimated by the Department of Labor of the United States for this country. Interestingly, during the domestic currency pegged, indexation in local currency was forbidden, and external indexes were used to adjust privatization contracts.

States). Third, by means of price monitoring[9] (such is the case of Australian and New Zealander airports). Finally, there are also other regulatory methods, with fewer cases, as the Canadian model of zero benefits (not-for-profit model), or hybrid models between price cap and cost-plus (such as the schemes in use in the airports of Paris, Copenhagen and Dublin).

The paper is organized as follows: section 2 briefly surveys the literature on the topic; section 3 describes the methodology and data we employed; section 4 presents the estimates DEA models, with and without environmental variables; section 5 discuss the results of the study; and finally in the section 6 we present the conclusions.

2. Literature review

The vast majority of the studies measuring efficiency of airports have used non-parametric methods to assess the level of efficiency, particularly DEA.

There are a variety of studies that can be highlighted, such as the pioneering article of Gillen and Lall (1997) on the efficiency of U.S. airports. Taking into account 21 airports in the period 1989-1993, and dividing the products it offers in airport ground services and air services, the authors consider two different DEA frontiers as the product being offered. Finally, Tobit regressions were estimated accounting on the effect of different dummy variables at efficiency level. The results show that the presence of a hub between flights and the number of ramps increase efficiency.

Parker (1999) investigates the impact of privatization in Britain taking as sample 22 airports privatized, concluding that this change did not produce striking changes in the efficiency of the 22 airports.

Early work that focused on techniques for analyzing nonparametric frontier did not include multiple products that can offer an airport (Martin-Cejas, 2002; Pells et al., 2001; Pells et al., 2003).

In an analysis of the efficiency of European airports, Pels, Nijkamp and Rietveld (2001 and 2003) compare the results obtained from DEA methods to those using stochastic frontier analysis (SFA). Their analysis shows that the stochastic frontier model that they consider reproduces the results of the DEA in a fairly reasonable way.

Kamp (2006) estimates efficiency of 16 airports in Germany for the period 1998-2004, which shows some heterogeneity in the results and several aspects to consider as the cost and use of the airport terminal and excess capacity of both side of the terminal and the air space.

Tovar and Martin-Cejas (2008), use stochastic frontier efficiency to study 26 Spanish airports between 1993 and 1999, obtaining the distance function of the parameters (inputs) estimates and then evaluate the input-oriented Malmquist productivity index to measure and decompose changes in productivity. With an average technical efficiency over 80% in the 26 airports examined, they found a significant difference in efficiency between the main airports of the land and island airports, the latter having an efficiency level above average. In this conclusion, there is a lot of influence on efficiency of the geographical location.

Barros (2008) uses a stochastic frontier analysis to analyze the effectiveness of 27 airports in Great Britain. The estimated results vary depending on whether you use a homogeneous or heterogeneous border, resulting in a higher average level of efficiency with the last one.

Barros, Managi and Yoshida (2008) study 16 Japanese airports between 1987-2005 by SFA. They use a random or heterogeneous stochastic frontier model in comparison of an

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[9] It is applied a Soft Regulation if and when the firm do not set high prices, or revenues obtained do not be considered disproportionate, or the quality levels fall. In such cases, it is triggered a clause that enables a more rigorous regulation in the long run.

homogeneous model. They conclude that random variables such as technology or major construction or other variables explain the variability of efficiency levels between airports.

Malighetti et al. (2009) focus on the relationship between the efficiency of the airports in the European Union and two factors: the strategic place they occupy in the European airport network and the intensity of competition from alternative airports in close geographic proximity. Focusing on an analysis with the DEA model, Simar and Wilson (2007) estimate the efficiency of the 57 biggest European airports by 2006. The results show that the importance of an airport in the European air network, positively affects the level of efficiency. The greater is the importance of the contribution of airport network development in an area, the higher the level of efficiency. At the same time, they reach to the conclusion that airports with higher passenger intensity (i.e. a movement greater than 10 million people per year) tend to have higher efficiency than those with lower intensity of passengers.

Ulutas (2008) estimates efficiency of 31 Turkish airports for the period 2004-2005, using a DEA analysis. One can see that major airports were very high levels of efficiencies, but the vast majority of airports were not acceptable efficiency levels. According to the author this may be due to the information gathered.

Barros and Dieke (2008) estimate a single DEA frontier in the analysis made on 31 airports in Italy in the period between 2001 and 2003. Adopting a methodology similar to that of Simar and Wilson (2007) estimate a truncated regression, thereby finding that the major airports tend to be more efficient and airports operated by private capital also tend to have more efficient results than their public counterparts.

Suzuki, Nijkamp, Pels and Rietveld (2009) analyze 19 European airports for the period 2003 through DEA, introducing trade variable in the study. This last variable does not affect the results on efficiency, but the authors say they should put some emphasis on developing this activity.

There is a lack of literature devoted to the study of the efficiency of Latinamerican airports, there are only a few works. Flor and de la Torre (2008) use DEA Malmquist input oriented to analyze the efficiency and total factor productivity of 11 Peruvian airports between 2002 and 2006. The results show that the airport conceded significantly increased their productivity, but these increases are due to increased traffic and the number of operations, i.e. an increase in demand. In turn it appears that in most airports fail to develop economies of scale that would allow a higher level of efficiency. Fernandez and Pacheco (2002) also apply DEA methods to analyze the efficiency of 35 Brazilian domestic airports in terms of passenger. Perelman and Serebrisky (2010) conducted a study encompassing major Latin American airports airports compared to US, Canada, Europe and Asia. They analyzed 148 airports for the period 2005-2006 through DEA model, assuming CRS and VRS. Only two airports are efficient regardless of whether you hold constant or variable returns to scale, both Brazilian airports. Globally, Latin American airports have acceptable yields compared with the rest of the world. In a second section of the paper they make a truncated regression to determine the causes of differences in efficiency. It concludes that airports that serve as hubs tend to be more efficient than the rest; airports located in cities with more than 5 million people have higher efficiency than other cities; the level of gross domestic product also positively affects the level of efficiency; and privately owned airports tend to have greater efficiency and increased revenue.

San Martino (2009) compares, using a DEA model, the relative efficiency of a sample of international airports, including the main Argentinean ones. His data came from the Airport Council International (ACI), an organization of conceded airports, and it is referred to the year 2007. The airports in the sample have similar structural features: they were conceded, they are regulated, they are subject to uniform security standards to operate, and also, they are subject to similar international regulations on airlines and passengers facilities. The better results are for airports with a yearly traffic exceeding 12 million passengers.

3. Methodology and data

Methodology

Data Envelopment Analysis (DEA) provides a comprehensive methodology to analyze the relative efficiency, to evaluate each airport and to measure their performance relative to the frontier of better practices. The airports, which fall into the outside surface, are considered efficient, while those who do not are inefficient. The analysis provides a measure of their relative (in) efficiency. The main advantage of this approach is that it requires no functional fit. The basic aspects of this methodology can be found in Coelli, Prasada-Rao and Battese (1998). A fuller treatment is found in Cooper, Seiford and Zhu (2004).

The selection of a particular model of DEA demands two decisions. The first one has to do with an assumption about returns to scale. There are basically two alternatives: constant returns to scale (CRS) and variable returns to scale (VRS). Secondly, the choice of a concept of distance involves the option for a direction for the model: the proportional input reduction holding constant the output level, the proportional increase in inputs given the output level, or no guidance at all. The theoretical specification of the input-oriented CRS, is a restricted optimization problem as follows:

$$(1) \qquad \min_{\theta,\lambda} \theta \qquad \text{subject to:} \qquad \begin{cases} y_j \leq \lambda \boldsymbol{Y} \\ \lambda \boldsymbol{X} \leq \theta x_j \end{cases}$$

Where $\boldsymbol{Y}$ is a matrix $N \times r$ outputs of the decision making units (i.e. airports) in the sample (N denotes the number of airports and r the number of outputs), $\boldsymbol{X}$ is an $N \times m$ matrix of inputs (m indexes inputs considered), $\boldsymbol{Z}$ is $N \times s$ matrix that contains all information on the S environmental variables of N units, y_j, x_j y z_j are the observed output vectors, inputs and environmental variables, respectively, of the unit under analysis, and finally, λ is a vector of intensity parameters (λ_1, λ_2, ..., λ_N) which allows the convex combination of observed inputs and outputs (so as to build the outside surface).

For an RVE model of any orientation, simply add an additional constraint to the above specifications:

$$(2) \qquad \Sigma_j \lambda_j = 1 \quad \text{para } j = 1, 2,\ldots, N.$$

This restriction ensures that an inefficient unit is compared only against decision units of similar size. Without this restriction, the unit under analysis can be compared with other materially greater or smaller, and the scale can be important.

Any of the above problems must be solved N times, once for each of the units in the sample. Efficiency measures obtained, and are known as Debreu-Farrell measures. The θ value obtained (one for each production unit), which we call θ* (where the '*' denotes optimal value) is the measure of efficiency of the airport under analysis. If the radial contraction of inputs is possible, the measure value is less than one ($\theta^*<1$), the production unit is inefficient, and $[(1 - \theta^*) \times 100]$ measures the percentage reduction in cost can be and inputs. For example, if $\theta^* = 0.80$, the production unit could reduce costs by 20%.

The VRS model is the most desirable because it does not restrict allowable returns to scale. However, also CRS versions were computed of all models, since in many cases, smaller and less productive airports tend to appear as 100% efficient if there were no comparators.

We choose to model the environmental variables (z) as neutral non-discretionary variables (on which the airport authorities have no control). In this option, each decision unit is only compared against a hypothetical airport that has the same operating environment that the firm under evaluation. The main advantage of this option is that it does not imply any a priori judgment on the direction of the influence of each environmental variable on efficiency.

The DEA index can be calculated in several ways.

In this study, we estimated an output-oriented, technically efficient (TE) DEA index, assuming that airports aim to maximize the profits resulting from their activity. In this context, inputs are exogenous and outputs endogenous, because of the competitive environment in which the units compete (Kumbhakar, 1987).

The CCR (or Charnes, Cooper, and Rhodes) efficient score model (1978) is probably the most widely used and best-known DEA model. It is the DEA model that assumes constant returns to scale (CRS) relationship between inputs and outputs. CCR measures the overall efficiency for each unit, namely aggregating pure technical efficiency and scale efficiency into one value (Gollani and Roll, 1989).

The BCC (or Banker, Charnes, and Cooper) efficient score model (1984) is a DEA model that assumes variable returns to scale (VRS) between inputs and outputs. It measures pure technical efficiency alone (Gollani and Roll, 1989). The efficiency score obtained with the BCC model gives a figure, which is at least equal to the number obtained using the CCR.

Scale efficiency score is obtained by dividing the aggregate CCR score by the technical efficient BCC score (Banker, 1984). A unit is scale-efficient when its size of operation is optimal. If its size is either reduced or increased, its efficiency will drop. Assuming that pure technical efficiency is attributed to managerial skills, the BCC scores are interpreted in that sense.

All the DEA scores used in the paper are called ratio models, because they define efficiency as the ratio of weighted outputs divided by the weighted inputs. They use a radial or proportionate measure to determine the technical efficiency. A unit's technical efficiency is defined by the ratio of the distance from the origin to the inefficient unit, divided by the distance from the origin to the composite unit on the efficient frontier.

The DEA score is between zero (0%) and 1 (100%). Units with DEA scores equal to 1 (100%) are efficient. A unit with a score of less than 100% is relatively inefficient, e.g. a unit with a score of 95% is only 95% as efficient as the best performing airports. Scores are relative to the other units, thus they are not absolute.

All technically efficient CRS (or constant return to scale) airports are also technically efficient in VRS (or variable returns to scale), signifying that the dominant source of efficiency is scale. CRS is assumed if an increase in a unit's input leads to a proportionate increase in its outputs. This signifies that no matter at what scale the unit operates, its efficiency will remain unchanged, assuming its current operating practices. Variable returns to scale exist when there are increasing returns to scale or decreasing returns to scale. Increasing returns to scale exist when an increase in a unit inputs yields a greater than proportionate increase in its outputs. Decreasing returns to scale exist when a decrease in a unit inputs yields lower than proportionate increase in output.

Data

To perform a proper appreciation of an efficient frontier to measure the performance of different production units, we have to describe the variables in use in the estimates. In order to estimate the frontier total factor productivity, we use a balanced panel of 31 airports managed by AA2000 between 2003 and 2007. The information (155 observations), was obtained through many sources including the official website of the company, and the ORSNA[10].

Three indicators that adequately describe operational activity at airports measure the output. They are the number of aircrafts, the number of passengers and the total cargo transported by air. In turn, four indicators measure inputs: number of employees, surface in square feet of runways, ramps and airport passenger terminals.

The combination of indicators ensures adherence to the DEA convention that the minimum number of unit's observations should not exceed three times the number of inputs and outputs. Moreover, we also observe the convention that the minimum number of units is equal to, or greater than, the product of the outputs and inputs. Using an output orientation, we can determine if an airport is capable of producing the same level of output with fewer inputs. The Table 1 describes the variables and presents its descriptive statistics (from both sources).

There are certain methodological problems that must be resolved before any analysis using the DEA method. We should define financial and physical measures of inputs and outputs. In the first ones (financial), there is a particular problem on inputs for the capital and its depreciation. Asset values, due to accounting procedures, vary considerably in a private company, as to in a public one. In the case of AA2000 airports, the land of the airports does not appear in the accounts, such as it is in the accounts of public airports. Furthermore, it should be noted that not all assets are depreciated in the same manner, differing from one airport to another, as also working capital costs vary greatly from one region to another, and are measured in different manners. Thus, the financial aspects will not be taken into account in this analysis. The determination of a viable physical measure of input is also difficult to perform, but data are more accurate about the capacity or surface of runways, terminals, ramps and other infrastructure. As well as the number of workers operating in the terminal, are confident (and uniformly accounted).

To measure the physical output we use number of planes, passengers and cargo. The first one does not distinguish between the sizes of the aircrafts, but this does not diminish the importance of measuring the efficiency of air operations. To standardize the number of passengers and cargo it is generally used the Work Load Unit (WLU), using a criterion of weight to normalize (for example, WLU = 1 passenger or 100 kg of cargo).

[INSERT TABLE 1 HERE]

4. Results (estimates)

In the Table 2, we see that 7 airports get top marks for the entire period under the BCC model; these are the Comodoro Rivadavia (COM), Formosa (FOR), General Pico (PIC), Mendoza (MEN), Puerto Madryn (MAD), Santa Fe (SFE) and Santa Rosa (SRA). Meanwhile, Aeroparque Jorge Newbery (NEW) and Ezeiza EZE), those with the greater flow of traffic have high efficiency levels, but not in all periods achieved the highest score. Other large airports, such as Cordoba (COR) and Bariloche (BAR), have a breakthrough in the efficiency level over the years, but remains far from the more efficient airports. In the case of Villa Reynolds (REY), it has a decrease in efficiency over the period, beginning with an efficiency of 1, and falling to 0.700. The collected information shows that the number of flights decreased to a level below half of what they received the first year of study, while the amount

[10] We found some differences in the data provided by AA2000 and the ORSNA, we opt to use the former. The qualitative results do not vary, even when the quantitative results are slightly different.

of cargo also fell sharply to 0. Rio Grande (RGR) is a special case, since its efficiency increases to reach the highest degree of efficiency in the second year and then begin to fall and remain well below that level. Another particular case is Reconquista (REC), where there was an increase in efficiency contemporaneous to the economic recovery. Although it never gets to have a considerable level of efficiency and following the fall in the number of passengers and flights decreases their efficiency.

Analyzing the average level of efficiency between 2003-2007 estimated using the CCR model, we can see that no airport received the highest level of efficiency, while only 6 airports obtained an efficiency level higher than 0.900 (NEW, EZE, COM, IGU, MEN, RGR). While some airports received very inefficient scores, lower than 0.400. The most extreme cases are Malargüe (MAL), San Juan (SJU) and Viedma (VIE). None of the airports with higher efficiency scores under BCC can reach similar performance under CCR (i.e. FOR, PIC, MAD, SFE, and SRA). In cases such as FOR, PIC, MAD, SFE and SRA, it is clear the difference between the results obtained with one model or another. The average efficiency in the CCR model decreases by 25% compared to the results obtained with the BCC model.

The scale efficiency achieved by dividing the performance coefficient of the CCR model and the performance coefficient of the BCC model, shows that only 8 airports have an scale efficiency superior than 0.900 (BAR, NEW, EZE, COM, COR, IGU, MEN, RGR).

[INSERT TABLE 2 HERE]

The next stage in our study consists in examining common denominators in the airport performance. The country is extended and with a low population density[11]. The capital city and its suburbs concentrate one third of the population. The diversity of climate and landscapes allows the existence of diverse sparse touristy destinations, from ski centers (BAR), to tropical falls (IGU), passing by arid mountain destinations (MEN or SAL). Other possible explanation of the domestic traffic has to be with politics and the federal organization of the country. Then we thought on three environmental variables: “capital” for the two metropolitan airports (EZE, NEW), “tourism” for the different touristy destinations, and “Province” for the provincial capitals. The remaining airports have more peculiar features, like being Air Force bases (REC, REY), very distant places (RGR) or an oilfield (COM), etcetera.

In Table 3 we can see the level of average efficiency with BCC model when introducing environmental variables "Tourism", "Capital" and "Province". The average efficiency increases regardless of which is the variable that is added to the model, as also lowers its standard deviation and dispersion coefficient. By analyzing one by one environmental variables it can be seen an increase in the amount of airports in the highest level of efficiency. From about 7 airports when none environmental variables are considered, to 3 new airports when we add the variable "Tourism". A distinctly tourist airport like Bariloche (BAR) has significantly increased its efficiency, but still does not reach optimum levels. Instead, Iguazú (IGU) airport, also mostly touristy, increases efficiency and yields on the frontier.

[INSERT TABLE 3 HERE]

[11] Eleven times the surface of Great Britain and two thirds of its population, to make a comparison. The country is also located in the far south of the globe, away from the main international routes.

By including the variable “Capital” in the model, the number of airports in the frontier increases by a single airport (NEW). The increase in efficiency is lower than that occurred when adding the variable "Tourism" to the model.

The last environmental variable is “Province”. In this case, 3 new airports reach the maximum level of efficiency. The vast majority of airports increased their efficiency by adding this environmental variable, obtaining similar results to the model with the variable "Tourism".

In the Table 4 we present the results of the BCC model expressed in frequency, and in the Table 5 the BCC model is estimated for all periods, enabling to see how the analyzed airports performed during this period. The CCR model is shown in an average way.

[INSERT TABLE 4 HERE]

[INSERT TABLE 5 HERE]

The efficiency of the airports of the sample in all cases exceeds the 0.401 levels, either with or without considering environmental variables. The average efficiency is around 0.782, with a standard deviation of 0.219. A 42% of the units have high efficiency in the BCC model without environmental variables, while 61% have a higher efficiency level of 0.801. The average efficiency with environmental variables increases, reaching 0.858 when the environmental variable is "Tourism", 0.820 when the variable is "Capital" and 0.846 when the variable is “Province”. Besides the standard deviation and the dispersion decreases, marking the highest level of efficiency, in the sum of all airports.

[INSERT TABLE 6 HERE]

The BCC efficiency scores presented in Tables 5, 6, 7 and 8 are average values for the period, but the CCR airports are analyzed across all years. The results are similar: almost all Argentinean airports display technical efficiency, but some of them do not display scale efficiency. The Table 5 presents the estimates with no environmental variables, while Tables 6, 7 and 8 include respectively the environmental variables “Tourism”, “Capital” and “Province”.

[INSERT TABLE 7 HERE]

[INSERT TABLE 8 HERE]

5. Discussion of the results

Gillen and Lall (1999) argue that in airports with inability to expand capacity through greater investment, but with strong demand pressures, there is a tendency to improve the utilization of available infrastructure, which has an impact on productivity of the airport. This does not come to appreciate in the case of Argentina's airports, which have great pressure on the demand side, but still there are cases where the efficiency drops throughout the years.

It appears that the efficiency of airports varies, but it is very clear that the efficiency varies widely with economic cycles and across the country's economy. The only airports that maintain similar results are EZE, NEW and COM.

It is also noted that these airports which maintain their efficiency despite economic fluctuations. In turn it can be seen as efficiency fluctuates throughout the period, becoming more efficient some airports by the end of the period under analysis, while others become more inefficient. The average efficiency tendency has some volatility, the average efficiency falls toward the end of the period.

AA2000 is envisaged that does not have a homogenous administrative culture through its various airports. However, as EZE and NEW accounts for 84% of the revenues of AA2000, according to Serebrisky and Presso (2002), the emphasis on the effectiveness of these two airports is a rational decision. It can be concluded that leading airports have some immunity to the economic crisis, but the smaller regional airports experimented more difficult to maintain their efficiency.

As the Argentina airports are single till regulated, this procedure combined with the polarization of the revenue in both the Buenos Aires airports may restrict the success of privatization. The possibility of cross-subsidization of the minor airports by the major ones is limited.

6. Conclusions

The main objectives of this paper are to measure the relative efficiency of Argentinean airports, and to infer possible regulatory consequences of the results. We pay attention to regional differences that could help the regulator in its task. At the same time, we try to determine which “environmental” variables (in the sense of particular conditions which are specific to different sets of airports) affect the relative efficiency of different airports. We thought on three environmental variables: “capital” for the two metropolitan airports, “tourism” for the different touristy destinations, and “Province” for the provincial capitals. The remaining airports have more peculiar features.

Of the DEA analysis we derive two broad conclusions. Firstly, significant differences in efficiency are prevalent in Argentinean airports. Secondly, best-practice calculations indicate that much of the Argentinean airports operate at a high level of efficiency during the period.

Therefore, the overall conclusion is that Argentinean airports are mixed managed during the period as far as technical efficiency is concerned. Moreover, dimension makes a difference and therefore, some airports have decreasing returns to scale, while others have increasing returns to scale. Those Argentinean airports with decreasing returns to scale (DRS) are too large in dimension. Scale dimension should be decreased if decreasing returns to scale prevail. Those airports with increasing returns to scale (IRS) are too small in dimension. Scale dimension should be increased if increasing returns to scale prevail. Those with CRS (constant returns to scale) have the adequate dimension.

There is some preponderance of the IRS on Argentine airports; even more so many of them are quite far from the production frontier of constant returns to scale. That is, to satisfy the growing demand for air transport services at those airports that have IRS, it is necessary to make some investments to increase the size of airports and thus achieve greater efficiency.

Tables

Table 1: Descriptive statistics (database AA2000)					
Variables	Definition	Average	Standard deviation	Max	Min
A. Outputs					
Number of aircrafts	Number of planes landing and taking off from the airport	8752	17720.8	84844	494
Number of passengers	Number of passengers arriving and departing from the airport	522869	1410404.4	7487779	834
Total cargo transported	Cargo tons arriving and departing from the airport	7013	31738.9	204909	0
B. Inputs					
Number of workers	Number of workers	37	68.3	372	1
Runways	Runway surface in square feet (database AA2000)	131310	84466.01	483897	15309
	Runway surface in square feet (database ORSNA)	132198	74368.5	436725	54000
Ramps	Ramp surface in square feet (database AA2000)	37672	93770.7	515900	315
	Ramp surface in square feet (database ORSNA)	37672	93770.7	515900	315
Airport passenger terminals	Airport passenger terminal surface in square feet (database AA2000)	9438	28668.5	162700	180
	Airport passenger terminal surface in square feet (database ORSNA)	6261	13232.3	71000	180
Source: Own elaboration on AA2000 and ORSNA.					

Table 2: Technical Efficiency Scores for Argentinean Airports.
BCC Model (yearly) and CCR Model (average). Period 2003-2007.

	BCC model (VRS)					Standard deviation	CCR model (CRS)	Scale Efficiency SE = CCR/avg BCC
	2003	2004	2005	2006	2007			
BAR	0,434	0,480	0,502	0,516	0,541	0,040	0,456	0,920
NEW	1,000	1,000	1,000	0,964	1,000	0,016	0,992	0,999
EZE	0,895	1,000	0,941	1,000	1,000	0,048	0,961	0,993
CAT	0,870	0,839	0,810	0,810	0,797	0,029	0,308	0,373
COM	1,000	1,000	1,000	1,000	1,000	0,000	0,991	0,991
COR	0,632	0,645	0,642	0,573	0,566	0,039	0,600	0,980
FOR	1,000	1,000	1,000	1,000	1,000	0,000	0,509	0,509
PIC	1,000	1,000	1,000	1,000	1,000	0,000	0,847	0,847
IGU	0,919	1,000	1,000	1,000	1,000	0,036	0,980	0,996
RIO	0,923	0,915	0,909	0,919	0,891	0,013	0,357	0,391
MAL	0,815	0,815	0,798	0,798	0,788	0,012	0,174	0,217
MAR	0,577	0,519	0,513	0,486	0,479	0,039	0,419	0,809
MEN	1,000	1,000	1,000	1,000	1,000	0,000	0,999	0,999
PAR	0,684	0,657	0,614	0,590	0,580	0,044	0,431	0,687
POS	0,792	0,859	0,802	0,807	0,756	0,037	0,478	0,593
MAD	1,000	1,000	1,000	1,000	1,000	0,000	0,490	0,490
REC	0,553	0,698	0,627	0,553	0,553	0,065	0,507	0,846
RES	0,405	0,446	0,400	0,408	0,376	0,025	0,257	0,630
RCU	0,596	0,596	0,596	0,596	0,596	0,000	0,223	0,373
RGA	0,945	1,000	0,933	0,958	0,974	0,026	0,911	0,947
RGR	0,952	1,000	0,840	0,909	0,715	0,111	0,722	0,803
SAL	0,418	0,457	0,431	0,433	0,517	0,039	0,398	0,879
SFE	1,000	1,000	1,000	1,000	1,000	0,000	0,328	0,328
SJU	0,501	0,504	0,502	0,507	0,506	0,003	0,197	0,391
SLU	0,887	0,918	0,903	0,888	0,831	0,033	0,352	0,397
SRA	0,924	0,924	0,929	0,937	0,924	0,006	0,353	0,380
SRO	1,000	1,000	1,000	1,000	1,000	0,000	0,691	0,691
SGO	0,748	0,763	0,758	0,755	0,762	0,006	0,336	0,444
TUC	0,515	0,550	0,462	0,470	0,465	0,039	0,425	0,862
VIE	0,481	0,484	0,486	0,483	0,481	0,002	0,152	0,315
REY	1,000	0,876	0,773	0,697	0,678	0,134	0,639	0,776
Average	0,789	0,805	0,780	0,776	0,767	0,027	0,532	0,673
Standard deviation	0,214	0,209	0,210	0,218	0,215	0,032	0,270	0,259
Dispersion	0,271	0,259	0,270	0,280	0,280	1,167	0,508	0,385
Median	0,887	0,876	0,810	0,810	0,788	0,025	0,456	0,691

Source: Own elaboration on AA2000 data.

Table 3: Efficiency levels without and with environmental variables

Airport	BCC model (VRS) without environmental variables	BCC model (VRS) with "Tourism" environmental variable	BCC model (VRS) with "Capital" environmental variable	BCC model (VRS) with "Province" environmental variable
BAR	0,495	0,647	0,639	0,832
NEW	0,993	0,997	1,000	0,997
EZE	0,967	0,968	0,988	0,967
CAT	0,825	1,000	0,825	1,000
COM	1,000	1,000	1,000	1,000
COR	0,612	0,992	0,991	0,991
FOR	1,000	1,000	1,000	1,000
PIC	1,000	1,000	1,000	1,000
IGU	0,984	1,000	0,984	0,992
RIO	0,911	0,969	0,930	1,000
MAL	0,803	0,803	0,803	0,851
MAR	0,515	0,855	0,597	0,596
MEN	1,000	1,000	1,000	1,000
PAR	0,625	0,785	0,625	0,641
POS	0,803	0,906	0,872	0,898
MAD	1,000	1,000	1,000	1,000
REC	0,597	0,597	0,602	0,600
RES	0,407	0,486	0,414	0,421
RCU	0,596	0,831	0,596	0,596
RGA	0,962	0,969	0,992	0,993
RGR	0,883	0,884	0,945	0,954
SAL	0,451	0,604	0,516	0,585
SFE	1,000	1,000	1,000	1,000
SJU	0,504	0,504	0,534	0,544
SLU	0,885	0,885	0,953	0,970
SRA	0,928	0,928	0,934	1,000
SRO	1,000	1,000	1,000	1,000
SGO	0,757	0,776	0,797	0,886
TUC	0,492	0,646	0,575	0,637
VIE	0,483	0,483	0,486	0,641
REY	0,805	1,000	0,805	0,805
Average	0,783	0,855	0,819	0,852
Standard deviation	0,210	0,176	0,197	0,185
Dispersion	0,268	0,205	0,240	0,217
Median	0,825	0,928	0,930	0,967

Source: Own elaboration on AA2000 data.

Table 4: Relative frequency in BCC models (VRS)				
	BCC	BCC	BCC	BCC
Airport efficiency	Without environmental Variables	Touristy place	Capital city	Province capital
Relative frequency	%	%	%	%
0-10%				
10.1-20%				
20.1-30%				
30.1-40%				
40.1-50%	16	6	6	3
50.1-60%	13	6	16	13
60.1-70%	6	10	10	13
70.1-80%	3	6	3	
80.1-90%	19	16	13	16
90.1-100%	42	55	52	55
Total %	100	100	100	100
Observations	31	31	31	31
Average	0,782	0,858	0,820	0,846
Standard Deviation	0,219	0,187	0,209	0,203
Dispersion	0,281	0,217	0,254	0,240
Source: Own elaboration on AA2000 data				

Table 5: Technical Efficiency Scores for Argentinean Airports.
CCR Model (yearly) and BCC Model (average). Period 2003-2007.

	CCR model (CRS)					BCC model (VRS)	Scale Efficiency SE = CCR/avg BCC	Returns to scale
	2003	2004	2005	2006	2007			
BAR	0,398	0,463	0,514	0,536	0,573	0,725	0,683	DRS
NEW	1,000	1,000	1,000	0,959	1,000	0,997	0,995	CRS
EZE	0,706	0,854	0,869	0,928	1,000	0,877	0,993	CRS
CAT	0,315	0,324	0,389	0,283	0,302	0,995	0,324	IRS
COM	1,000	1,000	0,953	1,000	1,000	1,000	0,991	CRS
COR	0,597	0,614	0,624	0,510	0,508	0,579	0,985	DRS
FOR	0,303	0,293	0,307	0,316	0,308	0,964	0,318	IRS
PIC	0,698	0,824	0,791	1,000	0,577	1,000	0,778	IRS
IGU	0,388	0,444	0,492	0,519	0,573	0,619	0,777	DRS
RIO	0,367	0,375	0,391	0,381	0,305	0,912	0,398	IRS
MAL	0,139	0,118	0,164	0,148	0,082	0,728	0,177	IRS
MAR	0,513	0,427	0,415	0,358	0,341	0,535	0,764	IRS
MEN	0,973	0,959	1,000	1,000	1,000	0,995	0,991	DRS
PAR	0,424	0,393	0,403	0,364	0,310	0,759	0,498	IRS
POS	0,150	0,199	0,219	0,232	0,187	0,825	0,239	IRS
MAD	0,670	0,454	0,465	0,565	0,542	1,000	0,539	IRS
REC	0,378	0,592	0,577	0,515	0,372	0,581	0,834	IRS
RES	0,132	0,195	0,189	0,197	0,162	0,455	0,384	IRS
RCU	0,224	0,265	0,282	0,289	0,223	0,699	0,367	IRS
RGA	0,650	0,710	0,569	0,563	0,583	0,762	0,805	DRS
RGR	0,897	1,000	0,921	0,992	0,900	0,987	0,954	IRS
SAL	0,817	0,938	0,851	0,854	1,000	0,900	0,991	IRS
SFE	0,246	0,308	0,292	0,269	0,279	1,000	0,279	IRS
SJU	0,171	0,177	0,171	0,177	0,178	0,489	0,357	IRS
SLU	0,306	0,373	0,390	0,358	0,191	0,776	0,413	IRS
SRA	0,289	0,286	0,355	0,345	0,382	0,908	0,365	IRS
SRO	0,575	0,607	0,684	0,766	0,480	1,000	0,622	IRS
SGO	0,448	0,522	0,507	0,504	0,553	0,867	0,584	IRS
TUC	0,517	0,557	0,459	0,468	0,448	0,644	0,760	IRS
VIE	0,168	0,174	0,192	0,162	0,110	0,486	0,331	IRS
REY	1,000	0,698	0,594	0,473	0,392	0,772	0,797	IRS
Average	0,499	0,521	0,517	0,517	0,479	0,801	0,622	
Standard Deviation	0,280	0,277	0,257	0,281	0,289	0,181	0,273	
Dispersion	0,561	0,531	0,497	0,543	0,603	0,226	0,438	
Median	0,424	0,454	0,465	0,473	0,392	0,825	0,622	

Source: Own Elaboration on AA2000 data. DRS = decreasing returns to scale; IRS = increasing returns to scale.

Table 6: Technical Efficiency Scores for Argentinean Airports.
CCR Model (yearly) and BCC Model (average). Period 2003-2007.

	CCR model (CRS) with "Tourism" environmental variable					BCC model (VRS) with "Tourism" environmental variable	Scale Efficiency SE = CCR/avg BCC	Returns to scale
	2003	2004	2005	2006	2007			
BAR	0,497	0,528	0,549	0,559	0,576	0,647	0,841	IRS
NEW	1,000	1,000	1,000	0,959	1,000	0,997	0,995	CRS
EZE	0,892	1,000	0,941	0,989	1,000	0,968	0,996	CRS
CAT	0,355	0,343	0,389	0,283	0,288	1,000	0,332	IRS
COM	1,000	1,000	0,953	1,000	1,000	1,000	0,991	CRS
COR	0,688	0,709	0,661	0,582	0,579	0,992	0,649	IRS
FOR	0,555	0,544	0,472	0,495	0,477	1,000	0,509	IRS
PIC	0,869	1,000	0,791	1,000	0,577	1,000	0,847	DRS
IGU	0,970	1,000	1,000	1,000	1,000	1,000	0,994	CRS
RIO	0,360	0,368	0,378	0,376	0,301	0,969	0,368	IRS
MAL	0,186	0,153	0,201	0,186	0,144	0,803	0,217	IRS
MAR	0,877	0,805	0,795	0,748	0,737	0,855	0,930	IRS
MEN	1,000	1,000	1,000	1,000	1,000	1,000	1,000	CRS
PAR	0,571	0,530	0,468	0,423	0,354	0,785	0,595	IRS
POS	0,493	0,575	0,544	0,571	0,461	0,906	0,583	IRS
MAD	1,000	1,000	1,000	1,000	1,000	1,000	1,000	IRS
REC	0,387	0,606	0,590	0,527	0,424	0,597	0,846	DRS
RES	0,269	0,342	0,308	0,321	0,247	0,486	0,610	IRS
RCU	0,195	0,228	0,245	0,251	0,194	0,831	0,268	IRS
RGA	0,906	1,000	0,869	0,882	0,900	0,969	0,940	DRS
RGR	0,855	0,952	0,636	0,740	0,425	0,884	0,802	IRS
SAL	0,440	0,493	0,450	0,442	0,542	0,604	0,783	IRS
SFE	0,308	0,367	0,335	0,309	0,320	1,000	0,328	IRS
SJU	0,217	0,216	0,189	0,183	0,180	0,504	0,391	IRS
SLU	0,329	0,392	0,405	0,370	0,266	0,885	0,397	IRS
SRA	0,307	0,304	0,376	0,366	0,411	0,928	0,380	IRS
SRO	0,639	0,674	0,759	0,850	0,533	1,000	0,691	IRS
SGO	0,282	0,338	0,331	0,341	0,389	0,776	0,433	IRS
TUC	0,461	0,497	0,434	0,442	0,423	0,646	0,698	IRS
VIE	0,167	0,159	0,184	0,148	0,104	0,483	0,315	IRS
REY	1,000	0,698	0,595	0,474	0,430	1,000	0,639	IRS
Average	0,583	0,607	0,576	0,575	0,525	0,855	0,657	
Standard Deviation	0,299	0,296	0,269	0,290	0,289	0,176	0,261	
Dispersion	0,513	0,487	0,467	0,504	0,549	0,205	0,398	
Median	0,497	0,544	0,544	0,495	0,430	0,928	0,649	

Source: Own Elaboration on AA2000 data.

Table 7: Technical Efficiency Scores for Argentinean Airports.
CCR Model (yearly) and BCC Model (average).
Period 2003-2007.

	CCR model (CRS) with environmental variable "Capital"					BCC model (VRS) with environmental variable "Capital"	Scale Efficiency SE = CCR/avg BCC	Returns to scale
	2003	2004	2005	2006	2007			
BAR	0,518	0,596	0,645	0,673	0,720	0,639	0,985	DRS
NEW	1,000	1,000	1,000	1,000	1,000	1,000	1,000	CRS
EZE	0,996	1,000	0,946	0,987	1,000	0,988	0,997	CRS
CAT	0,408	0,334	0,364	0,265	0,277	0,825	0,398	IRS
COM	1,000	1,000	0,953	1,000	1,000	1,000	0,991	CRS
COR	0,983	0,695	1,000	0,982	0,981	0,991	0,937	DRS
FOR	0,561	0,550	0,522	0,545	0,506	1,000	0,537	IRS
PIC	0,869	1,000	0,796	1,000	0,585	1,000	0,850	IRS
IGU	0,899	1,000	1,000	1,000	1,000	0,984	0,996	DRS
RIO	0,589	0,566	0,546	0,574	0,440	0,930	0,583	IRS
MAL	0,233	0,198	0,265	0,238	0,205	0,803	0,284	IRS
MAR	0,670	0,589	0,566	0,484	0,413	0,597	0,907	DRS
MEN	1,000	0,996	1,000	1,000	1,000	1,000	0,999	CRS
PAR	0,507	0,471	0,454	0,410	0,352	0,625	0,700	IRS
POS	0,669	0,671	0,634	0,538	0,404	0,872	0,664	IRS
MAD	0,586	0,402	0,412	0,500	0,584	1,000	0,497	IRS
REC	0,388	0,608	0,592	0,528	0,425	0,602	0,842	IRS
RES	0,273	0,305	0,300	0,305	0,205	0,414	0,667	IRS
RCU	0,195	0,228	0,245	0,251	0,194	0,596	0,373	IRS
RGA	1,000	1,000	0,959	0,986	1,000	0,992	0,997	CRS
RGR	0,897	1,000	0,926	1,000	0,645	0,945	0,940	IRS
SAL	0,451	0,493	0,470	0,487	0,598	0,516	0,969	DRS
SFE	0,323	0,391	0,381	0,378	0,371	1,000	0,369	IRS
SJU	0,322	0,334	0,317	0,338	0,329	0,534	0,614	IRS
SLU	0,536	0,672	0,687	0,601	0,431	0,953	0,611	IRS
SRA	0,327	0,416	0,476	0,496	0,452	0,934	0,463	IRS
SRO	0,709	0,735	0,841	0,954	0,547	1,000	0,757	IRS
SGO	0,442	0,510	0,494	0,486	0,528	0,797	0,617	IRS
TUC	0,579	0,647	0,511	0,534	0,537	0,575	0,978	DRS
VIE	0,199	0,239	0,261	0,226	0,150	0,486	0,442	IRS
REY	1,000	0,698	0,595	0,474	0,430	0,805	0,776	IRS
Average	0,617	0,624	0,618	0,621	0,558	0,819	0,734	
Standard Deviation	0,278	0,266	0,256	0,281	0,275	0,197	0,234	
Dispersion	0,450	0,426	0,414	0,452	0,493	0,240	0,319	
Median	0,579	0,596	0,566	0,534	0,506	0,930	0,757	

Source: Own Elaboration on AA2000 data.

Table 8: Technical Efficiency Scores for Argentinean Airports.
CCR Model (yearly) and BCC Model (average).
Period 2003-2007.

	CCR model (CRS) with environmental variable "Provincia"					BCC model (VRS) with environmental variable "Provincial"	Scale Efficiency SE = CCR/avg BCC	Returns to scale
	2003	2004	2005	2006	2007			
BAR	0,491	0,567	0,617	0,643	0,689	0,832	0,720	DRS
NEW	1,000	1,000	1,000	0,959	1,000	0,997	0,995	CRS
EZE	0,887	1,000	0,941	0,989	1,000	0,967	0,996	CRS
CAT	1,000	1,000	1,000	1,000	1,000	1,000	1,000	IRS
COM	1,000	1,000	0,953	1,000	1,000	1,000	0,991	CRS
COR	0,675	0,672	0,700	0,633	0,623	0,991	0,667	IRS
FOR	1,000	1,000	1,000	1,000	1,000	1,000	1,000	IRS
PIC	0,869	1,000	0,791	1,000	0,577	1,000	0,847	IRS
IGU	0,899	1,000	1,000	1,000	1,000	0,992	0,987	DRS
RIO	1,000	1,000	1,000	1,000	1,000	1,000	1,000	IRS
MAL	0,186	0,153	0,201	0,186	0,144	0,851	0,205	IRS
MAR	0,521	0,434	0,422	0,364	0,352	0,596	0,699	IRS
MEN	1,000	1,000	1,000	1,000	1,000	1,000	1,000	
PAR	0,710	0,677	0,631	0,592	0,580	0,641	0,995	IRS
POS	0,793	0,882	0,813	0,822	0,756	0,898	0,913	IRS
MAD	0,586	0,402	0,412	0,500	0,549	1,000	0,490	IRS
REC	0,387	0,606	0,590	0,527	0,424	0,600	0,841	DRS
RES	0,405	0,460	0,403	0,413	0,376	0,421	0,977	IRS
RCU	0,195	0,228	0,245	0,251	0,194	0,596	0,373	IRS
RGA	0,958	1,000	0,949	0,972	0,986	0,993	0,979	DRS
RGR	0,855	0,952	0,636	0,740	0,425	0,954	0,749	IRS
SAL	0,508	0,550	0,522	0,532	0,635	0,585	0,939	IRS
SFE	0,308	0,367	0,335	0,309	0,320	1,000	0,328	IRS
SJU	0,503	0,506	0,504	0,509	0,508	0,544	0,930	IRS
SLU	1,000	1,000	0,982	0,954	0,882	0,970	0,994	IRS
SRA	0,307	0,304	0,376	0,366	0,411	1,000	0,353	IRS
SRO	1,000	1,000	1,000	1,000	1,000	1,000	1,000	IRS
SGO	0,850	0,878	0,870	0,863	0,894	0,886	0,983	IRS
TUC	0,550	0,594	0,478	0,488	0,484	0,637	0,814	IRS
VIE	0,641	0,641	0,641	0,641	0,641	0,641	1,000	IRS
REY	1,000	0,698	0,595	0,474	0,430	0,805	0,776	IRS
Average	0,712	0,728	0,697	0,701	0,674	0,852	0,824	
Standard deviation	0,273	0,276	0,261	0,273	0,279	0,185	0,237	
Dispersion	0,383	0,380	0,375	0,389	0,414	0,217	0,288	
Median	0,793	0,698	0,641	0,643	0,635	0,967	0,939	

Source: Own Elaboration on AA2000 data.

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