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# Economic efficiency analysis of Italian airports: an SFA approach.

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# Abstract

This work offers a methodological framework to analyze the efficiency of the Italian airport system. An SFA analysis is performed on 23 airports for the period 2006-2015. Alternative model specifications are used to assess the robustness of the conclusions. Strong evidence of the existence of a significant level of inefficiency in the industry is found. Small and large airports are found to have substantially different cost structures, and therefore should be studied separately. Ownership structure does not seem to play a major role as a cost driver.

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# 1 Introduction

The last decades have seen a sharp increase in air traffic of both passengers and cargo. This, together with the privatization of airports and of air companies, changed the market into a very competitive one. Nowadays, a strong airport industry is fundamental to connect a country both internally and externally, and even more so for its economic development. This leads many stakeholders, particularly policymakers, to watch the economic performance of airports with great interest. In order to guide these stakeholders in their decisions, it is important to be aware of the cost structure and the efficiency of the airport sector.

Our work wants to contribute to current literature with a representative view of the state of the efficiency of the Italian airport industry. While previous works have mostly used non-parametric methods for this purpose, we have used a stochastic frontier model to estimate a long term cost function which we then used to evaluate the efficiency of 23 Italian airports, observed over the 10 years going from 2006 to 2015.

The work is structured as follows:
**Section 2** describes the characteristics of the Italian airport system;
**Section 3** provides a review of current literature;
**Section 4** introduces the methodology used in this work;
**Section 5** discusses the obtained results;
**Section 6** presents our conclusions.

# 2 The Italian airport system

## 2.1 Deregulation and privatization in the European airway industry

In the last couple of decades, the airport industry in Europe has undergone great changes. Up until the late ‘80s, it was characterized by public ownership of airports and carriers. Flagship carriers were allowed to travel between countries which shared bilateral agreements, which restricted air service between two countries to a single carrier from each country per route. The late ‘80s and the ‘90s signaled a period of privatization and deregulation, started by the complete privatization of British Airways, in 1987, and following the deregulation in the United States, begun in 1978 with the Airline Deregulation Act. This process was marked by a series of directives introduced by the European Union:

- In 1987, 1990 and 1992, three legislative packages were introduced with the aim of replacing the bilateral agreements system, lowering barriers to market access and allowing free pricing;
- Council Directive 96/67/EC, which liberalized ground-handling services (e.g. passenger and baggage handling, fueling, cleaning of aircrafts);
- Directive 2009/12/EC, which created a framework for airport charges, requiring consistency with costs, transparency, non-discriminating-treatment of different airlines, and delegating to member states the task to set up independent supervisory authorities.

At the beginning of the deregulation process, the flagship carriers’ response was to obstruct market entry of new contenders via lobbying. This practice wasn’t very effective, because it could not stop the entry of already existing carriers that operated in different geographic areas. A second strategy was that of dumping, which in the United States had brought a lowering in the number of contenders. In Europe this strategy proved to be less effective, since flagship carriers received public subsidies, which prevented market exit. Even merges and acquisitions didn’t play such an important role as in the United States, as carriers mostly followed the route of commercial agreements and alliances.

The liberalization process lead to the market entry of new carriers, the emergence of the low cost business model, the development of new airports in the whole continent, and the diffusion of point to point connections as an alternative to the hub and spoke model. These changes also had important consequences to the airport operators' business model. Prior to privatization, airports were publicly owned, and the operators could shift the cost of inefficiencies to the flagship carrier, again publicly owned. The final customer, paying for the ticket, ended up bearing the cost of the inefficiencies of the whole system. Liberalization increased the competition downstream, which put pressure on airport operators to lower their charges since carriers had become more price sensitive. Also, the different business model of low cost carriers (LCC), which sought cheaper regional airports and avoided the largest hubs, pushed local authorities toward competing for their presence, which would in turn boost the local economy.

The shift of airport ownership from completely public to partially or totally private, and the increased market competition, created an incentive to be more efficient in order to lower charges and attract more carriers, and thus passengers. Commercial activities kept gaining an increasing relevance in the business model of airport operators, contributing by 2014 to 41% of total revenue.[1]

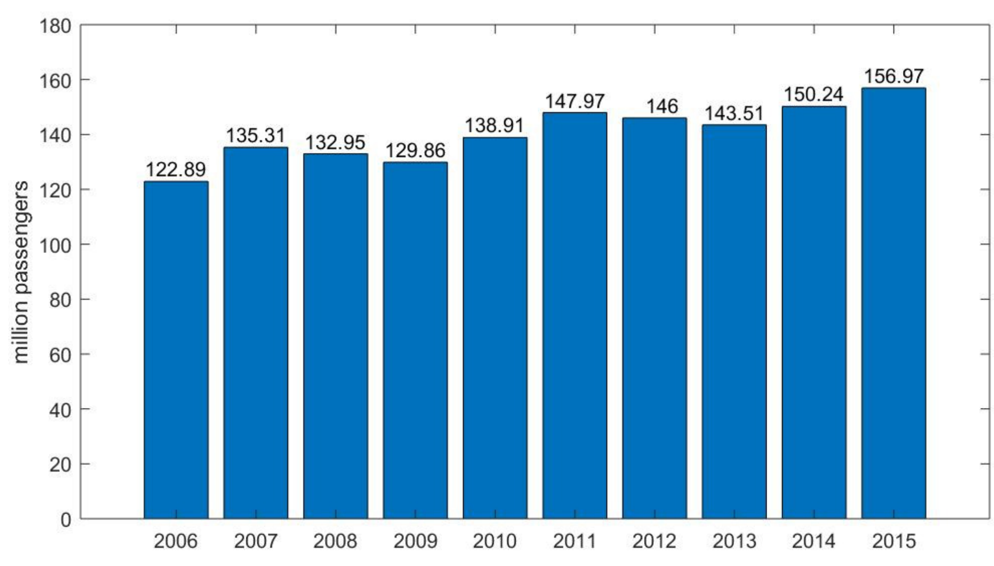
In Italy, prior to liberalization, the market was characterized by a monopoly of the flagship carrier Alitalia. The deregulation process allowed the entry of new European companies, which filled the regional niches left unoccupied up to that point. These companies were mostly low cost operators, which by 2015 generated 48.38% of passenger traffic. The effects of the liberalization were similar to what happened in the rest of the European Union, with a large increase in the number of routes available and a sharp decrease in average price.

[1] European Commission. Annual Analyses of the EU Air Transport Market 2016.

## 2.2 The Italian airport industry

The airport system is responsible for the creation of 4.1% of the European Union's GDP. Italy places a little under the average, with a contribution of 3.6%.[2] Aside from their economical relevance, airport infrastructures are an important factor of interconnectivity. This is especially significant in a country characterized by having an irregular geography and a vast insular area. Italy is the 5th country in Europe by number of airports open to commercial traffic, with 44 infrastructures. Nevertheless, it presents a peculiarity in the number of medium-smalls airports, which is unusually high in the European landscape. This leads to a high concentration, with the 5 largest airports comprising 55.6% of total passenger traffic and 54% of aircraft movements in 2015.[3] The reason behind the high number of medium-small airports is to be found on the one hand in the presence of various economic and touristic focal points, on the other hand in the absence of adequate ground infrastructures and their uneven distribution.

Figure 1- Passenger and cargo traffic in Italy

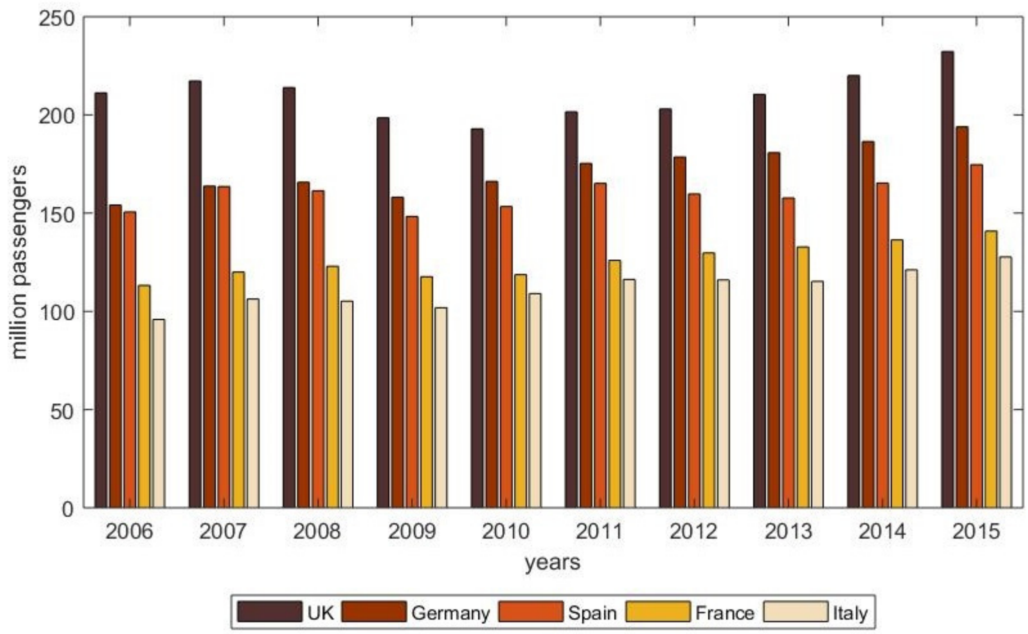



Source: Elaboration of Eurostat data.

[2] CDP, Cassa Depositi e Prestiti. (2015). Il sistema aeroportuale italiano.
[3] This and the following national traffic data is publicly available from ENAC (Italian Civil Aviation Authority) at www.enac.gov.it.

In 2015, passenger traffic in Italian airports reached 157 million, the 5th highest in the European Union after the United Kingdom, Germany, Spain and France.[4] Of this number, 62.4% is international traffic, 74.8% of which is intra-EU. The ten years going from 2006 to 2015 registered an increase in traffic, although a reduction occurred during the years 2008 and 2009 due to the financial crisis, and a light contraction was registered in 2011 and 2012 as well. Nevertheless, the compound annual growth rate (CAGR) at which passenger traffic grew was of 2.9%, above that of 2.4% of the EU.

Figure 2 - Passenger traffic in the most populous EU countries




Source: Elaboration of Eurostat data[5].

If compared with the other EU countries, cargo traffic in Italy is quite underdeveloped. In 2015, Italy was 6th with 916 thousand tonnes of goods, while Germany moved more than 4.5 million tonnes and the UK 2.4 million tonnes.[6] The lesser importance that air cargo traffic assumes for the country is reflected by the growth rate, with a CAGR over the observation period of 0.91%, while that of the EU was 1.80%.

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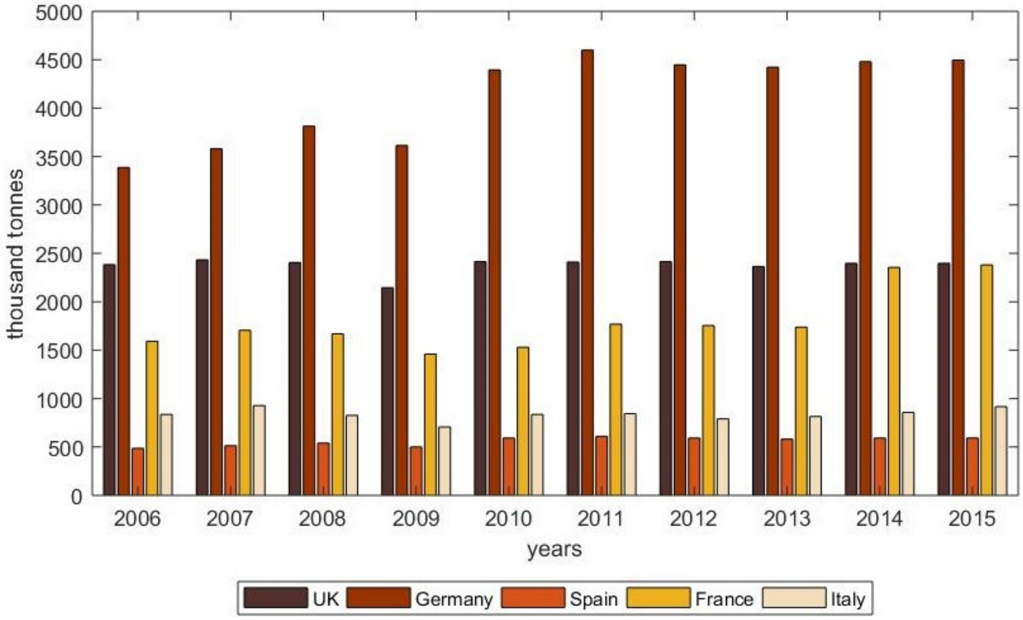
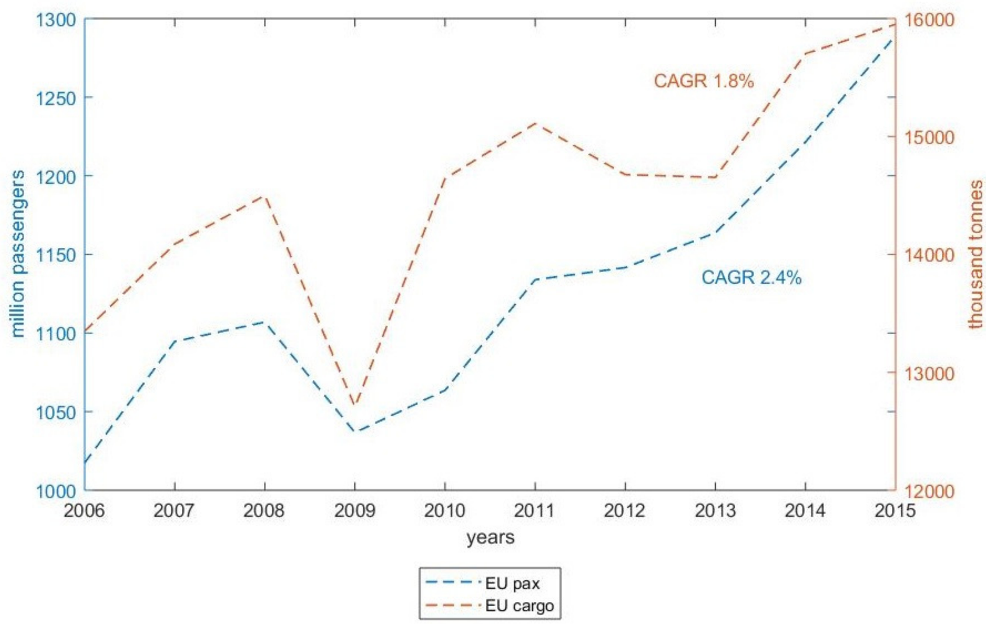
[4] Data on EU countries is publicly available from EUROSTAT at www.ec.europa.eu/eurostat/.
[5] Due to the different measuring methods, data from Eurostat cannot be confronted directly with data taken from ENAC.
[6] All numbers include goods and mail.

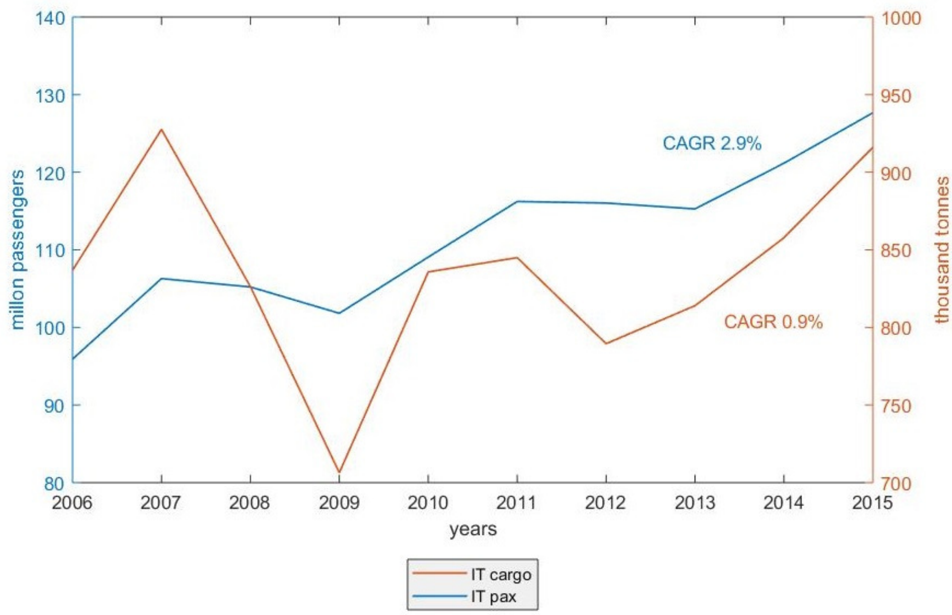
Figure 3 - Cargo traffic in the most populous EU countries




Source: Elaboration of Eurostat data.

Figure 4 - A comparison of passenger and cargo growth in Italy and in the EU






Source: Elaboration of Eurostat data.

The 27 airports included in our analysis represent 98.77% of national passenger traffic, 98.21% of aircraft movements and 99.28% of cargo traffic, therefore we can reasonably assume that they are a good approximation of the whole Italian airport system. From now on, all that will be said will be in regard to these 27 airports, which will be generally referred to as ‘the airports’ or ‘the Italian airport system’. The two airports of the city of Rome, Fiumicino and Ciampino, being managed by the same group, have been considered as a single system in the analysis. The same is true for the two airports of the city of Milan, Malpensa and Linate. This was necessary because the data collected could not be separated at the single airport level, and also to make this analysis comparable with previous ones, which used the same grouping.

The airports have been grouped in four categories, according to their size and following the EU classification:

Large Community Airport (LCA), with over 10 million passengers per year;

National Airports (NAA), between 5 and 10 million passengers per year;

Large Regional Airports (LRA), between 1 and 5 million passengers per year;

Small Regional Airports (SRA), fewer than 1 million passengers per year.

Table 1 - Airport grouping by size class

| Airport | IATA Code | Class |
|---|---|---|
| **Bergamo** | BGY | LCA |
| **Milan Linate and Malpensa** | LINMXP | LCA |
| **Rome Fiumicino and Ciampino** | FCOCIA | LCA |
| **Bologna** | BLQ | NAA |
| **Catania** | CTA | NAA |
| **Napoli** | NAP | NAA |
| **Venice** | VCE | NAA |
| **Alghero** | AHO | LRA |
| **Bari** | BRI | LRA |
| **Brindisi** | BDS | LRA |
| **Cagliari** | CAG | LRA |
| **Florence** | FLR | LRA |
| **Genova** | GOA | LRA |
| **Lamezia** | SUF | LRA |
| **Olbia** | OLB | LRA |
| **Palermo** | PMO | LRA |
| **Pisa** | PSA | LRA |
| **Torino** | TRN | LRA |
| **Trapani** | TPS | LRA |
| **Treviso** | TFS | LRA |
| **Verona** | VRN | LRA |
| **Ancona** | AOI | SRA |
| **Brescia** | VBS | SRA |
| **Lampedusa** | LMP | SRA |
| **Pantelleria** | PNL | SRA |
| **Pescara** | PSR | SRA |
| **Trieste** | TRS | SRA |

Source: Elaboration of ENAC data.

The data of 2015 shows how 73% of passenger traffic was generated by airports that had more than 5 million passengers per year (NAA and higher). Traffic distribution for the year 2015 is as follows:

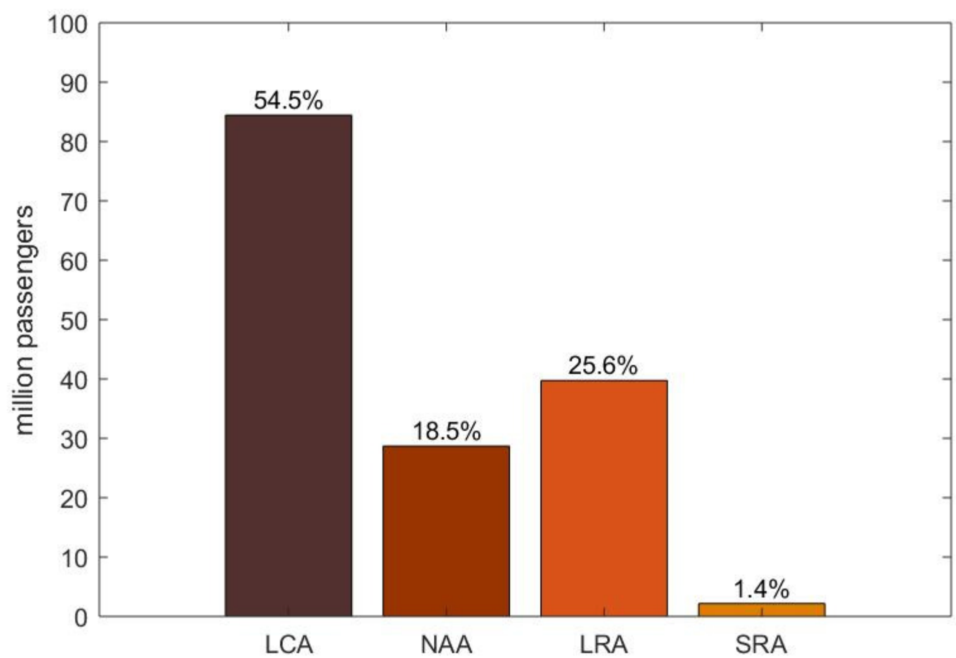
The 3 LCA airports registered 84.4 million passengers, accounting for 54.5% of national traffic;

The 4 NAA airports registered 28.7 million passengers, accounting for 18.5% of national traffic;

The 14 LRA airports registered 39.7 million passengers, accounting for 25.6% of national traffic;

The 6 SRA airports registered 2.2 million passengers, accounting for 1.4% of national traffic.

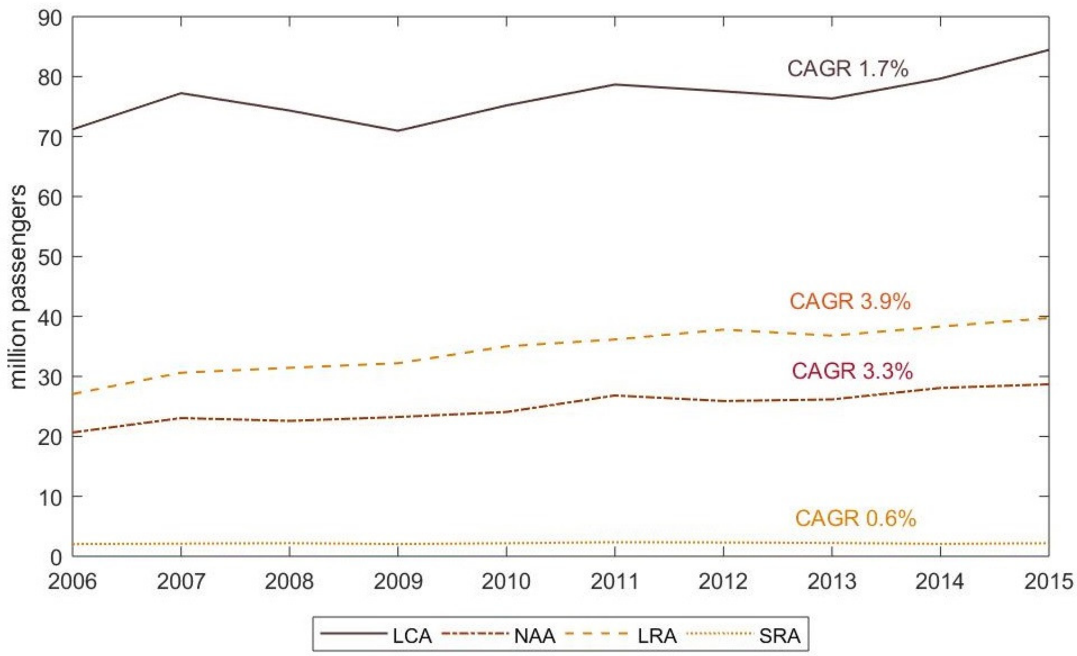
Figure 5 - Distribution of passengers by airport size class in 2015




Source: Elaboration of ENAC data.

Just like in the rest of Europe, passenger traffic in Italy was greatly influenced by the entry of LCC and the diffusion of high-speed rail. The years following the liberalization process witnessed an increasing penetration of low cost operators, their market share going up from 21% in 2003 to 48.38% in 2015. These carriers favored regional airports, which granted lower costs and a lower competition from the flagship carrier Alitalia. These are the airports that saw the biggest increase in passenger traffic during the years going from 2006 to 2015. Figure 6 shows how LRA and NAA airports' growth was above the average with a CAGR of 3.9% and 3.3% respectively, LCA airports lagged behind with a CAGR of 1.7% and SRA registered the smallest increase in traffic, only 0.6%. The CAGR of the industry was 2.5%.

Figure 6 - Evolution of passenger traffic by airport size class




Source: Elaboration of ENAC data.

The data on cargo traffic reveals how 96% of volume is attributable to LCA and NAA airports. Cargo distribution for the year 2015 is as follows:

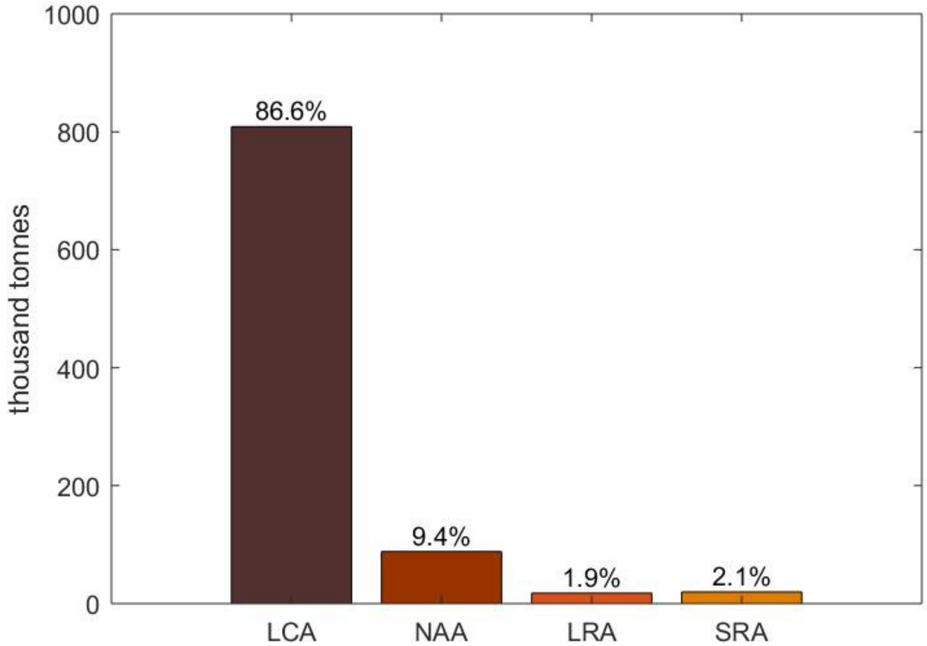
The 3 LCA airports moved 808.6 thousand tons of cargo, accounting for 86.6% of total volume. The airport system of Milan Linate and Malpensa alone accounted for 526.9 thousand tons, 56.4% of national volume;

The 4 NAA airports moved 88.2 thousand tons of cargo, accounting for 9.4% of total volume;

The 14 LRA airports moved 17.7 thousand tons of cargo, accounting for 1.9% of total volume;

The 6 SRA airports moved 19.8 thousand tons of cargo, accounting for 2.1% of total volume.

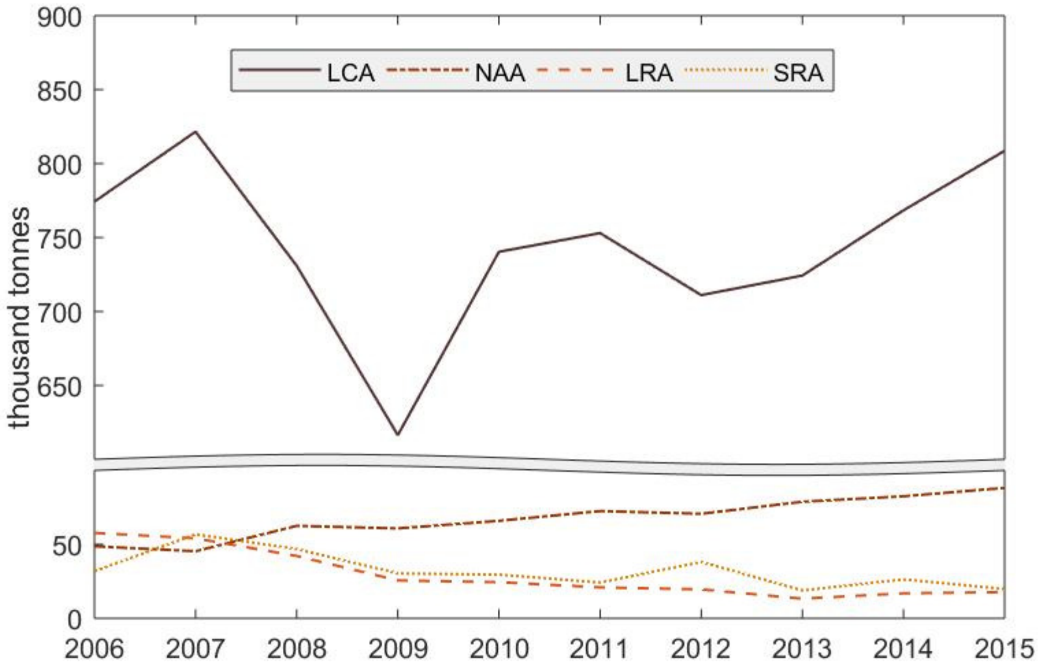
Figure 7 - Distribution of cargo traffic by airport size class in 2015




Source: Elaboration of ENAC data.

Over the observation period, from 2006 to 2015, the volume of air cargo traffic grew at a CAGR of 0.24%. Figure 8 shows how only NAA airports registered a significant increase in volume, with a CAGR of 6.1%. LCA airports recorded a very small growth, with a CAGR of 0.4%. SRA and LRA airports were in the negative, with a CAGR respectively of -4.7% and -11.1%.

Figure 8- Evolution of cargo traffic by airport size class




Source: Elaboration of ENAC data.

## 2.3 Price regulation in Italy

Aeronautical charges paid by airline companies are mainly of two types: landing fees for the use the airplanes make of the airfield, and charges for the use the passengers make of the terminal building. The sum charged as landing fee is usually based on the plane's maximum take-off weight, while the sum charged for using the terminal building depends on the flight being domestic, intra-EU or extra-EU.[7]

Up until the year 2000, aeronautical charges were periodically updated by the Ministry of Transportation (Ministero dei Trasporti, MIT). These charges, being sorts of taxes paid for the use of state-owned infrastructures, were identical for every airport, regardless of its size and the actual costs it sustained. From then, the regulatory framework was changed many times. Starting from 2009, some airports subscribed with the Italian Civil Aviation Authority (Ente nazionale per l'aviazione civile, ENAC) an agreement, called 'programme contract', which planned capital expenditures and adjusted charges to costs actually sustained. The airports which did not sign this agreement got their charges adjusted for inflation, but not to actual costs. The intervention of the Transport Regulation Authority (Autorità di regolazione dei Trasporti, ART) put some order to existing regulation. The Delibera ART n. 64/2014 introduced a differentiation in regulation according to airport traffic, lowering its impact the lesser the passenger volume. The ART identified three size classes: over 5 million passengers per year, between 3 and 5 million passengers per year, and under 3 million passengers per year. The reason behind this differentiated approach was to protect consumers in cases where actual market power existed, without overcomplicating procedures for airport operators and reducing costs related to regulation in cases where market power did not arise.

The framework by the ART is applied to all airport operators, and its effect was added to previous regulation put in place by ENAC. The only exception lies for the operators of Rome, Milan and Venice, which are still regulated by their respective programme contracts. In these cases, charges are decided by the airport operator following the pricing models

[7] Bel and Fageda (2009)

provided by ART, while the level of investments are established in the programme contract. The coexistence of two regulatory bodies is an exception in the European landscape.

A recurring theme in the field of airport price regulation has been whether a single till or a dual till approach should be used in setting aeronautical charges. The debate centers on how regulation of aeronautical services (e.g. aircraft take-off, landing, gangway, provision of terminal services to passengers and airlines) should deal with airports' revenues from commercial services (e.g. earnings from car parking or the rent of retail spaces). Under a single till approach, profit from an airport's non-aeronautical activities are subtracted from the revenue requirement for aeronautical services before determining the level of aeronautical charges. Under a dual till approach, the regulator omits entirely non-aeronautical activities from its calculation. Therefore, under single-till regulation, commercial revenues cover a portion of the airport's overall fixed costs, so that the single till price-cap for aeronautical services is reduced accordingly. The single till approach mimics the dynamics of a competitive market better than dual till, forcing airports that do not have a substantial market power to respond to competitive pressures by subsidizing aeronautical activities with non-aeronautical profits, leading to more economically efficient outcomes.[8]

In Italy, a dual till approach was introduced by the ART: The Delibera ART n. 64/2014 established that non-aeronautical activities must not be considered when determining aeronautical charges. Therefore, under a dual till approach, revenues from aeronautical activities are defined as the sum of the return on capital invested[9], depreciation costs and operating costs.

[8] See Czerny (2006), Bilotkach et al. (2012) and Elliott (2015). This picture may change when talking about congested airports, but a single till regulation might remain advantageous.
[9] Calculated as weighted average cost (WACC) times the regulatory asset base (RAB).

## 2.4 The ownership structure of Italian airports

Historically, the airport sector has been characterized by a prevalence of public capital in the ownership structure of management companies. This was due to the strategic importance of the airport as a national asset and its contribution to the economic development of a region; the fact that small-sized airports often are structurally unprofitable but essential for the life of small communities; the capital intensive nature of the business and its long payback time. Nevertheless, in the last twenty years, policymakers have incentivized the entrance of private capital in the airport industry, consistent with European guidelines.

In Italy, this process started in 1997 with the privatization of Napoli Capodichino, and it was more recently fueled by the need for public authorities to find resources following the financial crisis. In 2011, the municipality of Milan sold 30% of its shares of SEA – the company which manages Milan Linate and Malpensa – to the private equity fund F2i. In 2013, Atlantia became the majority shareholder of Aeroporti di Roma – which manages Rome Fiumicino and Ciampino - owning 95.9% of its shares. As of 2016, 14% of Italian airports are fully public, while most of the rest have mixed public-private ownership.[10]

Finding the required resources to finance interventions in this sector requires particular attention in order to allow an appropriate allocation of public resources and of private capital, keeping in mind the opportunity costs related to public contribution.

Another important development, happening in parallel to the privatization process, has been the commercialization of the airport industry. The increase in the competitiveness of the market forced airports to become leaner, to push themselves in the strife for traffic growth and route development, to boost efficiency and service quality, and to find the best way to finance investments. As a consequence, even fully public airports are becoming 'corporatized', that is, structured as independent commercial entities. 78% of fully public European airports fall under this category.[11]

From the analysis of the ownership structure of Italian airports, it emerges how private stakeholders are showing a growing interest in investing in the national airport sector. It is interesting to notice how the presence of private capital decreases as the airport size class decreases. LCA and NAA airports are the ones registering a higher penetration of private

[10] Airports Council International. The Ownership of Europe's Airports 2016.
[11] See note 10.

capital. On the other hand, SRA airports register a negative trend, with an increase in public intervention during recent years, probably due to the effects of the economic crisis.

Table 2 - The ownership structure of Italian airports in 2015

| Airport | IATA Code | Size Class | % Public Ownership[12] |
|---|---|---|---|
| **Alghero** | AHO | LRA | 100.0% |
| **Ancona** | AOI | SRA | 98.9% |
| **Bari** | BRI | LRA | 100.0% |
| **Bergamo** | BGY | LCA | 40.3% |
| **Bologna** | BLQ | NAA | 86.1% |
| **Brescia** | VBS | SRA | 57.0% |
| **Brindisi** | BDS | LRA | 100.0% |
| **Cagliari** | CAG | LRA | 95.2% |
| **Catania** | CTA | NAA | 100.0% |
| **Florence** | FLR | LRA | 32.0% |
| **Genova** | GOA | LRA | 85.0% |
| **Lamezia** | SUF | LRA | 68.0% |
| **Lampedusa** | LMP | SRA | 100.0% |
| **Milan Linate and Malpensa** | LINMXP | LCA | 55.7% |
| **Napoli** | NAP | NAA | 25.0% |
| **Olbia** | OLB | LRA | 20.0% |
| **Palermo** | PMO | LRA | 98.6% |
| **Pantelleria** | PNL | SRA | 12.7% |
| **Pescara** | PSR | SRA | 100.0% |
| **Pisa** | PSA | LRA | 32.0% |
| **Rome Fiumicino and Ciampino** | FCOCIA | LCA | 4.1% |
| **Torino** | TRN | LRA | 23.0% |
| **Trapani** | TPS | LRA | 61.3% |
| **Treviso** | TFS | LRA | 8.3% |
| **Trieste** | TRS | SRA | 100.0% |
| **Venice** | VCE | NAA | 10.0% |
| **Verona** | VRN | LRA | 57.0% |

Source: Elaboration on AIDA data.

[12] In the analysis, Chambers of Commerce were considered as public authorities, following Europe Airports Council International (2016).

# 3 Literature review

The present chapter offers a review of recent work on airport efficiency. A brief comment on each paper follows, underlining the methodology used and some of the insights drawn by the authors. In studying previous works, specific attention has been paid to the parameters used in the specification of the econometric model. The methodology, inputs and outputs used in each paper are summed up in the following table, which was used as a reference in the specification of our model.

Pels et al. (2001) worked with a sample of 34 European airports observed from 1995 to 1997, and used data envelopment analysis (DEA) to determine technical efficiency scores, which were then compared with measures obtained by means of a stochastic production frontier. Their study concluded that most European airports operated under increasing returns to scale. Their follow-up study, Pels et al. (2003), which again used DEA and stochastic frontier analysis (SFA), found that airports on average operate under constant return to scale for aircraft movements and increasing return to scale for passengers, and that a negative correlation exists between airport size and its return to scale. Following Starkie (2001), they suggested that, for many large airport, scale economies may not be the source of market power.

Martín-Cejas (2005) estimated the technical efficiency of 31 Spanish airports with data from 1997, discovering a much higher return to scale for cargo rather than passengers. Craig et al. (2005) used a symmetric generalized McFadden (SGM) cost function with a sample of 52 USA airports observed from 1972 to 1992, investigating the effect of governmental structure on technical and allocative efficiency and the rate of technical change. The authors found that single purpose authorities have a significant cost advantage over city operated airports, and present substantial higher level of technical efficiency.

Oum et al. (2008) applied a stochastic frontier analysis with a sample made up of an unbalanced panel of 109 airports around the world, with data ranging from 2001 to 2004. The cost frontier model was specified in a translog form and estimated using a Bayesian approach. The aim of the work was to study the effect of the ownership model on the efficiency, the results indicated that a full private or full public ownership is associated to lower costs.

Barros (2008a) used a random parameters frontier model to estimate the technical efficiency of a sample of 27 UK airports during the years 2000-2005, focusing on heterogeneity among airports. In a subsequent study, Barros (2008b) applied a stochastic cost frontier method to a sample of 12 Portuguese airports observed from 1990 to 2000, including a time trend to account for and disentangle technical change over a long time period.

Martín and Román (2009) used a Markov Chain Monte Carlo (MCMC) simulation to estimate a stochastic frontier analysis model to evaluate the efficiency of Spanish airports, from a sample of 37 airports observed in the period going from 1991 to 1997. Their conclusion was that large airports are more efficient than smaller ones, and that the presence of important economies of scale made the constant pricing scheme adopted in Spain not suitable from an economic point of view.

Abrate and Erbetta (2010) used a parametric input distance function to evaluate the efficiency of a sample of 26 Italian airports observed over a six-year period (2000-2005). Their approach allowed to obtain parameter estimations without having to rely on the hypothesis of cost minimization and without the requirement of input price data, which are a limit of traditional cost function estimation. The aim of the work was to quantify the possible synergies between the aeronautical, handling and commercial operations, reporting evidence toward outsourcing of handling operations as a valid managerial strategy.

Curi et al. (2010) and Curi et al. (2011) applied DEA with the Simar and Wilson's two-stage bootstrapping to investigate efficiency determinants. In their first study, a dataset made up of 36 Italian airports with data ranging from 2001 to 2003 was used. In the second one, 18 Italian airports were observed over the period going from 2000 to 2004. Among their findings, they reported that public airports are more efficient than mixed ownership or completely private ones, and that Italian airports are generally characterized by low levels of efficiency.

Table 3 - Summary of studies on airport benchmarking

| Authors | Data | Methodology | Inputs | Outputs |
|---|---|---|---|---|
| Pels et al. (2001) | 34 European airports; 1995-1997 | DEA, Stochastic production frontier | Air Transport Movements (ATM) model: number of runways (length in DEA), number of aircraft parking positions at terminal, remote aircraft parking position, total airport area (DEA only)<br>Air Passenger Movements (APM) model: number of baggage claim units, number of aircraft parking positions at terminal, remote aircraft parking position, number of check-in desks (DEA only), terminal size (DEA only) | ATM model: total number of aircraft movements<br>APM model: total number of passengers |
| Pels et al. (2003) | 34 European airports; 1995-1997 | DEA, Stochastic production frontier | Air Transport Movements (ATM) model: number of runways, number of aircraft parking positions at terminal, remote aircraft parking position, total airport area<br>Air Passenger Movements (APM) model: predicted value of ATM (actual value in DEA), number of baggage claim units, number of | ATM model: total number of aircraft movements<br>APM model: total number of passengers |

| Authors | Data | Methodology | Inputs | Outputs |
| --- | --- | --- | --- | --- |
| | | | aircraft parking positions at terminal, number of check-in desks, terminal size | |
| Martín-Cejas (2005) | 31 Spanish airports; 1997 | Stochastic (long run) cost function | Price of labor, price of capital | Number of passengers, amount of cargo |
| Craig et al. (2005) | 52 US airports; 1970-1992 (unbalanced panel) | SGM shadow (long run) cost function | Price of labor, price of capital, price of materials | Number of flights |
| Oum et al. (2008) | 109 airports in Asia, Australia-New Zealand, Europe, North America; 2001-2004 (unbalanced panel) | Stochastic (short run) cost frontier | Price of labor, price of soft cost input (purchasing power parity as proxy), number of runways (fixed input), passenger terminal area (fixed input) | Number of passengers, number of aircraft movements, non-aeronautical revenues |
| Barros (2008a) | 27 UK airports; 2000-2005 | Stochastic heterogeneous (long run) cost frontier (with random parameters associated to outputs) | Price of labor, price of capital-premises, price of capital-investment | Number of passengers, number of aircraft movements |
| Barros (2008b) | 13 Portuguese airports; 1990-2000 | Stochastic (long run) total cost frontier, with trend allowing for technical change | Price of labor, price of capital | Sales to planes, sales to passengers, non-aeronautical fees |
| Martín, Román (2009) | 37 Spanish airports; 1991-1997 | Stochastic (long run) cost frontier | Price of labor, price of capital, price of materials | Number of aircraft movements, work load units (WLU, which is equivalent to one passenger or 100kg of cargo) |

| Authors | Data | Methodology | Inputs | Outputs |
|---|---|---|---|---|
| Curi et al. (2010) | 36 Italian airports; 2001-2003 | DEA and two stage-bootstrapping | Labor costs, capital costs, price of other inputs | Number of passengers, number of aircraft movements, tons of cargo, aeronautical revenues, handling receipts, commercial revenues |
| Abrate, Erbetta (2010) | 26 Italian airports; 2000-2005 | Parametric input distance function | Labor costs, soft costs, apron area dedicated to aircraft parking, total airport surface | Number of passengers, handling revenues, commercial revenues |
| Curi et al. (2011) | 18 Italian airports; 2000-2004 | DEA and two-stage bootstrapping | Physical model: number of employees, number of runways, apron size<br>Financial model: labor costs, other costs, airport area. | Physical model: number of passengers, number of aircraft movements, tons of cargo<br>Financial model: aeronautical revenues, non-aeronautical revenues |

# 4 Methodology

## 4.1 Efficiency analysis

The concept of efficiency is quite broad and it encompasses different aspects. What we refer to in this work as economic efficiency, following Fabbri et al. (1996), is the joint effect of two factors: technical and allocative efficiency. Technical efficiency can be described as the use of the minimum amount of inputs to produce a given amount of output (input-oriented efficiency) or, conversely, the production of the maximum output given the inputs (output-oriented efficiency). Allocative efficiency measures a firm's success in choosing the input mix which grants the minimum cost. From now on, when generally talking of efficiency, we will refer to the product of these two factors.[13] For this definition to be meaningful, a way to measure efficiency is needed. In the economic literature, the study of the efficiency of a decision making unit (DMU, which in our case is represented by the single airport) has been undertaken using three main approaches: total factor productivity (TFP), data envelopment analysis (DEA) and stochastic frontier analysis (SFA).

TFP is the most straightforward, as it uses a simple ratio of output over input to measure the performance of the DMU. When multi-output and/or multi-input DMUs are considered, a weighted average must be taken, generally using price information as basis for calculating weights. Due to its very simplistic approach, this method is lacking in explanatory power. Another limit is the impossibility to decouple inefficiency into different types, which requires the use of more advanced techniques.

The other two approaches, DEA and SFA, require the construction of a cost or production frontier, and have a considerably higher data requirement than TFP. Following Farrell (1957), efficiency estimation is treated as a comparative assessment of the performances of different DMUs. These methodologies are based on the estimation of a best-practice frontier, against which actual performances are evaluated.

[13] See Farrell (1957) or Färe et al. (1985) for an in-depth analysis.

DEA is by far the most common method used in airport benchmarking. Being a non-parametric method, it uses linear programming for constructing best-practice frontiers. This offers the great advantage of not needing the specification of a functional form, which would require establishing in advance a fixed number of parameters to explain the structure of the production set. This allows for a very flexible approach that can be easily generalized. Another reason behind its common use is the fact that it does not require to assume a specific behavior from actors, like cost minimization. A big drawback of this method is the fact that it does not account for randomness: The distance of the DMU's performance from the frontier is entirely treated as inefficiency.[14] This makes it by nature a descriptive methodology, not an inferential one.

SFA overcomes some of the limitations of DEA, but in doing so it requires a larger set of assumptions to be made. This paragraph gives an overview of parametric techniques in general, to give the reader an intuitive idea of how they work. The SFA method and our model in particular will be discussed in detail in the next subchapter.

The parametric approach is based on building functional connections between the output set and the input prices on one side, and the production costs of each DMU on the other. The method works in two stages. In the first stage, a production or cost function is estimated, defining an average relationship between observed input and output data. In the second stage, the frontier is built by transposition of the function drawn in the first stage. This requires a translation resulting in all observation being located above the function. The construction of an economic efficiency frontier by translation generates residuals all with positive sign (the opposite is true for production frontiers). Inefficiency can then be measured as the distance of the DMU's performance, represented as a point above the frontier, from the frontier itself. Such a measure of inefficiency reflects the deterministic nature of this type of frontier. It is possible however to adopt a stochastic approach, which takes into account the fact that the selected parameters cannot fully explain this shift from the optimum. In this case, residuals are treated as random variables. Each observation will be represented as a point whose distance from the frontier depends not only on inefficiency, but also on a noise term. Hence, parametric models may use either a general deterministic approach or a stochastic one. In the first instance, all observations will be placed on the

[14] See Barros and Dieke (2008) and Curi et al. (2011) for an example on how authors have tackled this limitation.

frontier or above it. In the second instance, observations can be located above or below the deterministic frontier, according to the value of the noise term.
It is important to keep in mind that a best-practice frontier built from a sample cannot be interpreted as the best-practice frontier of the whole industry: If the sample contains only inefficient DMUs, the estimated frontier will be quite different from the actual industry's frontier. Its reliability does not go beyond the selected sample of DMUs.

In our analysis, we chose to use an SFA approach. The main advantage this method offers is its flexibility, which allows to deal with factors exogenous to management's control, errors in data collection, and it lessens problems deriving from an incomplete specification of the model. Furthermore, knowing the cost structure of a DMU allows for the study of scale and scope economies. A last reason was that it has been adopted less frequently than DEA, so that it felt like a more useful addition to the literature.

## 4.2 SFA in detail

SFA was introduced by the pioneering works of Aigner et al. (1977) and Meeusen and Van den Boreck (1977). The stochastic frontier approach is based on the idea that no DMU can perform better than the best-practice frontier, and that deviations from it represent inefficiencies. The method is based on the specification of a regression model having a composite residual made of two terms: a noise term, which captures measurement errors and specification errors, and a one-sided disturbance term, which represents inefficiency. Both production and cost frontiers have been employed, the former representing the maximum amount of output that can be obtained by using a set of inputs, the latter representing the minimum cost sustained to produce a set of outputs given the prices of the inputs needed in the production. We distinguish between cross-sectional data models, were the dataset is made up of observations of different DMUs at a given time, and panel data models, where the observations are taken over multiple time periods for the same DMUs. Stochastic frontier models are generally estimated by maximum likelihood-based approaches, with the main objective being making inference about the inefficiency term and the frontier parameters.

The production cost of DMU *i* at time *t* can be expressed as:

$$C_{it} = \mathrm{C}(\boldsymbol{Y_{it}}, \boldsymbol{W_{it}})e^{\varepsilon_{it}}$$
$$\varepsilon_{it} = v_{it} + u_i$$
$$i = 1, \dots, N$$
$$t = 1, \dots, T$$

where $C_{it}$ is a scalar representing the total cost, $\boldsymbol{Y_{it}}$ is a vector of outputs, $\boldsymbol{W_{it}}$ is a vector of input prices, $v_{it}$ is the noise term, and $u_{it}$ is the inefficiency term. The model can be written as:

$$C_{it} = \alpha + \boldsymbol{Y'_{it}\beta} + \boldsymbol{W'_{it}\varphi} + \varepsilon_{it}$$
$$\varepsilon_{it} = v_{it} + u_i$$
$$v_{it} \sim N(0, \sigma_v^2)$$
$$u_i \sim F$$

where $C_{it}$, $\boldsymbol{Y_{it}}$ and $\boldsymbol{W_{it}}$ are now expressed as logarithms, $\boldsymbol{\beta}$ and $\boldsymbol{\varphi}$ are vectors of parameters to be estimated. $v_{it}$ and $u_i$ are assumed to be independent of each other and identically distributed throughout observations. Regarding the distribution of the inefficiency term, which is required in order for the model to be estimable, the most common ones used in literature are the half-normal, the exponential, the truncated normal and the gamma distributions.

The model is usually fit by using maximum likelihood methods, but ordinary least squares or generalized method of moments can both be used, although they are generally inefficient. Stochastic frontier analysis is based on a sequential approach. In the first step, the estimates of the parameters of the model $\widehat{\boldsymbol{\Theta}}$ are evaluated through the maximization of the log-likelihood function $\ell(\boldsymbol{\Theta})$, with $\boldsymbol{\Theta} = (\alpha, \boldsymbol{\beta}', \boldsymbol{\varphi}', \sigma_v^2, \sigma_u^2)'$.[15] In the second step, point estimates of inefficiency can be determined by evaluating the mean or the mode of the conditional distribution $f(u_i|\hat{\varepsilon}_{it})$, with $\hat{\varepsilon}_{it} = \ln C_{it} - \alpha - \ln \boldsymbol{Y}'_{\boldsymbol{it}}\boldsymbol{\beta} - \ln \boldsymbol{W}'_{\boldsymbol{it}}\boldsymbol{\varphi}$. The derivation of the likelihood function requires to assume $v_{it}$ and $u_i$ to be independent. In general, numerical-based or simulation-based techniques are required to calculate it. The second step is needed because estimating the model parameters allows to obtain the residuals $\hat{\boldsymbol{\varepsilon}}$, but it does not let us decouple the noise term from the inefficiency term. In order to do this, we use the mean or the mode of the conditional distribution of $\boldsymbol{u}$ given $\boldsymbol{\varepsilon}$.[16] After obtaining the point estimates of $\boldsymbol{u}$, we can derive estimates of the economic efficiency as

$$\text{Eff} = \exp(-\hat{\boldsymbol{u}})$$

with $\hat{\boldsymbol{u}}$ being either $\mathbb{E}(\boldsymbol{u}|\hat{\boldsymbol{\varepsilon}})$ or $\mathbb{M}(\boldsymbol{u}|\hat{\boldsymbol{\varepsilon}})$.

Although panel data for a sufficient timeframe can often be hard to obtain, they offer a substantial advantage over the use of cross-sectional data. First, they allow to relax strong distributional assumptions for the $\boldsymbol{u}$ term when repeated observations on a sample of DMUs are available. In addition, while with cross-sectional data the inefficiency cannot be estimated consistently since the variance of $\mathbb{E}(\boldsymbol{u}|\hat{\boldsymbol{\varepsilon}})$ or $\mathbb{M}(\boldsymbol{u}|\hat{\boldsymbol{\varepsilon}})$ does not go to zero as the

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[15] As pointed by Fabbri et al. (1996), other parametrizations have been used in the literature, e.g. $\boldsymbol{\Theta} = (\alpha, \boldsymbol{\beta}', \boldsymbol{\phi}', \sigma^2, \lambda)'$ with $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\lambda = \sigma_u/\sigma_v$.

[16] See Jondrow et al. (1982) for an in-depth analysis.

number of DMUs in the sample increases, with panel data observations are taken over multiple time periods for the same DMUs, leading to consistent estimations of $u_i$ as $T \rightarrow \infty$.[17]

The model specification we gave treats the $\boldsymbol{u}$ term as a random variable, and is therefore referred to as a random-effect model. Panel data allows also to specify fixed-effect models. Fixed-effects models treat $u_i$ as non-random, making it instead a DMU-specific intercept parameter to be estimated along with $\boldsymbol{\beta}$ and $\boldsymbol{\varphi}$. The model can be written as:

$$C_{it} = \alpha_i + \boldsymbol{Y}'_{it}\boldsymbol{\beta} + \boldsymbol{W}'_{it}\boldsymbol{\varphi} + v_{it}$$
$$\alpha_i = \alpha + u_i$$

with $u_i \geq 0$. While the same assumptions as before apply to $v_i$, no distributional assumption is required for $u_i$, which can also be correlated to the error term and the regressors. The estimation of the inefficiency term is performed as follows:

$$\hat{\alpha} = \max_i \hat{\alpha}_i$$
$$\hat{u}_i = \hat{\alpha} - \hat{\alpha}_i$$

This implies that at least one DMU is assumed to be perfectly efficient, and the performances of the other DMUs are measured relative to the efficient ones. Fixed-effects models apply the within transformation, meaning that all data is expressed as deviation from the DMU's mean. This entails that all time-invariant effects are eliminated.
Fixed-effect models have the advantage of simplicity and of not relying on distributional assumptions for the $u_i$. However, as pointed out by Kumbhakar and Lovell (2000), the inefficiency term in these models captures the effects of all phenomena that vary across DMUs, but do not vary with time for each DMU (e.g. regulatory environment).

Stochastic frontier models can be further differentiated according to the hypothesis regarding the inefficiency term being either time-invariant or time-variant. In the previous formulation, we have expressed the $u_i$ term as being time-invariant. Such assumption should always be questioned. Although empirical analysis shows that indeed there are cases where

[17] See Kumbhakar and Lovell (2000) for an in-depth analysis

the efficiency does not vary with time, this should not be taken as a given, especially when the length of the time period is substantial. Among the time-invariant models, the ones proposed by Pitt and Lee (1981) and Battese and Coelli (1988) have seen a wide usage in the literature. These models mainly differ with regard to the assumption on the distribution of $\boldsymbol{u}$. The first one assumes $\boldsymbol{u}$ to follow a half normal distribution, while the second one assumes a truncated normal distribution. In both cases, the parameters are estimated through maximum likelihood. Different models have been proposed to express the inefficiency term as time-varying. Kumbhakar (1990) defines the time dependency of the inefficiency term as

$$u_{it} = \frac{1}{1 + \exp(\lambda t + \gamma t^2)} \times u_i$$
$$u_{it} \sim N^+(0, \sigma_u^2)$$

His model requires the estimation of two parameters only, and it easily allows to test the hypothesis of time-invariant inefficiency by setting $\lambda = \gamma = 0$. Battese and Coelli (1992) proposed a similar model, called 'time decay', where the inefficiency term takes the form of

$$u_{it} = \exp[-\eta(t - T)] \times u_i$$
$$u_{it} \sim N^+(\mu, \sigma_u^2)$$

Both these specifications represent the temporal pattern of $u_{it}$ as being DMU-invariant. Although other authors proposed formulation where each DMU has its own temporal pattern of inefficiency, these require the estimation of a large number of parameters. Cornwell et al. (1990) proposed a time-varying fixed-effects model with DMU-specific slope parameters as

$$u_{it} = \omega_i + \chi_i t + \lambda_i t^2$$

which is more flexible than the previous two, but requires the estimation of $N$ x 3 parameters. What these models have in common is that the intercept of the curve $\alpha$ is the same across DMUs. As Belotti et al. (2013) pointed out, if time-invariant unobservable factors exist, their effect would be captured by the inefficiency term, thus leading to biased estimations of $\boldsymbol{u}$. To address this problem, Greene (2005) proposed a time-varying model where $\alpha$ depends on the DMU, as follows:

$$\ln C_{it} = \alpha_i + \ln \boldsymbol{Y}'_{it}\boldsymbol{\beta} + \ln \boldsymbol{W}'_{it}\boldsymbol{\varphi} + \varepsilon_{it}$$

This specification allows to decouple DMU-specific time-invariant unobserved heterogeneity from the time-varying inefficiency term. However, part of the time-invariant unobserved heterogeneity should be considered inefficiency, so that whether disentangling these two terms is appropriate should be questioned. In our analysis, these methods will be tested and commented, in order to choose the most appropriate specification according to our scope and data.

Finally, SFA requires the selection of a functional form by which to approximate the cost frontier. In the literature, the most common choice has been the translog, which we can express as:

$$\ln \hat{C}_{it} = \alpha + \sum_j \beta_j \ln Y_{jit} + \sum_j \varphi_j \ln W_{jit} + \frac{1}{2}\sum_j \sum_k \gamma_{jk} \ln Y_{jit} \ln Y_{kit} + \sum_j \sum_k \delta_{jk} \ln Y_{jit} \ln W_{kit} + \frac{1}{2}\sum_j \sum_k \psi_{jk} \ln W_{jit} \ln W_{kit} + v_{it} + u_{it}$$

It represents a second order approximation of an unknown cost frontier, obtained through a Taylor series expansion of the logarithmic transformation about a vector $\boldsymbol{o}$.[18] The independent variables are expressed as deviations from the expansion vector $\boldsymbol{o}$. Since generally the mean is used as the approximation point, this results in the following normalization: $\ln Y_{it} - \ln \bar{Y}$, $\ln W_{it} - \ln \bar{W}$. In the approximation point, the translog function is a perfect representation of the unknown cost frontier. As we move away from $\boldsymbol{o}$, some approximation errors may appear.

The cost function has to be: non-decreasing, continuous, linearly homogeneous and concave with respect to input prices, and non-decreasing with respect to outputs. These regularity conditions need to be checked after the model has been estimated, with the exception of the homogeneity condition, which can be imposed a priori as:

[18] See Christensen et al. (1973) for details.

$$\sum_j \varphi_j = 1$$

$$\sum_k \psi_{jk} = 0, \sum_k \delta_{jk} = 0, \forall\, j$$

The translog functional form offers many advantages: Compared to other flexible functional forms, it requires the estimation of fewer parameters; differently than traditional functional forms like Cobb-Douglas, the translog allows for economies of scale to change with the amount of output.

The downside of using a translog functional form is that the number of parameters to be estimated explodes as the number of considered output measures or input prices increases. This in turn limits the number of degrees of freedom and may lead to multicollinearity.

## 4.3 Model specification

Our dataset contains balanced panel data on 23 Italian airports, observed from 2006 to 2015. Financial data were collected from balance sheets published by airport operators on their websites or obtained from the database AIDA, while data about traffic comes from ENAC and Assaeroporti websites.[19] Although chapter 2 presented traffic data, size classification and ownership structure of 27 airports, some of them were excluded from the efficiency analysis due to inconsistency of data or lack thereof. The airports of Bari and Brindisi were dropped from the dataset because the financial statements of Aeroporti di Puglia, the operator of the two airports as well as the ones of Foggia and Taranto, did not disaggregate costs and revenues at the single airport level. The same happened with the airports of Brescia and Verona. Further studies could try to include the whole airport system in the sample. In order to be able to confront financial data relative to different years, all the monetary variables were expressed in 2006 prices by using the annual consumer price indices published by the Italian National Institute of Statistics (ISTAT).

There is no consensus in airport literature about the appropriate cost model to be used for efficiency benchmarking, therefore our choice was guided by previous authors' choices, a production process rationale, econometric reasons, but also trial and error. The estimation of the cost model requires the definition of three types of variables: outputs, input prices, and control variables. The adequate specification of a multiproduct cost function poses a delicate problem in the definition of relevant outputs. Indeed, it requires a trade-off between the inclusion of the highest number of factors that could possibly describe the supply side, and the need to limit output measures so that the model can properly be estimated. Following Pels et al. (2003) and Abrate and Erbetta (2010), at first we had chosen to describe airport activities as separated into aeronautical, handling and commercial. Lack of data forced us to use a simpler differentiation into aviation and non-aviation activities.

The most common measures of aviation activities in the literature are passengers number, aircraft movements number, and volume of cargo. Cargo traffic has very low relevance for most Italian airports, with the exception of Milan and Rome. Therefore, we opted to combine

[19] AIDA is a database containing financial data on Italian companies. ENAC website can be reached at www.enac.gov.it. Assaeroporti is the Italian association of airport management companies. Its website can be reached at www.assaeroporti.com.

two output measures, number of passengers and cargo volume, into a single aggregate measure: work load unit (WLU), defined as one passenger or 100kg of cargo.[20] Since no physical output measure could be used as a proxy of non-aviation activities, revenues from non-aeronautical services (to which we refer to also as commercial revenues) were also included.

Regarding the choice of inputs, they were divided in three categories: labor, capital, and 'others'. The price of labor was calculated as the ratio of total labor expenses over the number of workers. As noted by Fabbri et al. (1996), this is not ideal, since the full-time equivalent (FTE) employees would be a more accurate measure than the number of workers. This is especially true since the airport sector is characterized by a large use of part-time workers. Another problem could occur if the average salary is not representative of the cost of the standard employee of the firm, due to the presence of outliers. However, the lack of more data forced us to calculate labor price as previously stated. The price of capital is typically problematic to evaluate. Again, lack of detailed data on the actual cost of capital made us opt for the sum of depreciations and financial costs to be used as a proxy. These were divided by total terminal area, a purely technical factor, to determine price of capital. The term 'others' is a non-labor-non-capital input price. It was calculated as the sum of expenditures for materials, services and the use of third parties' assets, divided by the number of aircraft movements.

Aside from outputs and input prices, some variables were added to check for airport characteristics that may influence the inefficiency estimation: the number of runways and the terminal area; a dummy variable that controls for the effect of ownership form, which assumes the value 1 in case of a majority public ownership; the international passenger traffic over total traffic ratio. It is to be noted that the only data available with regard to number of runways and terminal area was relative to the year 2014. These terms were therefore considered as fixed, although such an assumption has to be accepted skeptically with a timeframe of 10 years.

An important assumption that comes with this econometric approach is that of cost minimization by relevant actors. Albeit the majority of Italian airports is mostly publicly

[20] A similar solution has been adopted by Martín and Román (2009).

owned, and thus could potentially pursue goals different from the minimization of total costs, the fact that they are structured as independent commercial entities makes this hypothesis less likely. Nevertheless, such an assumption leaves much room for debate, and it is important to be aware of the fact that is implicit in our analysis.

Table 4 - Summary statistics[21]

| | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
|---|---|---|---|---|---|---|---|---|---|---|
| **Output measures** | | | | | | | | | | |
| **Number of WLUs** | 5.384 | 5.885 | 5.735 | 5.582 | 5.944 | 6.276 | 6.200 | 6.150 | 6.446 | 6.759 |
| **(millions)** | (9.921) | (10.743) | (10.197) | (9.540) | (10.196) | (10.609) | (10.309) | (10.159) | (10.715) | (11.271) |
| **Commercial revenues** | 26.424 | 28.315 | 28.071 | 26.923 | 27.310 | 27.276 | 24.194 | 23.457 | 23.030 | 23.869 |
| **(millions €)** | (61.351) | (64.701) | (62.758) | (59.276) | (61.746) | (61.110) | (49.194) | (47.910) | (47.248) | (48.943) |
| **Aircraft movements** | 56.955 | 61.185 | 58.311 | 54.846 | 56.567 | 57.143 | 55.566 | 52.953 | 53.416 | 53.750 |
| **(thousands)** | (97.080) | (101.728) | (95.611) | (85.562) | (89.816) | (90.410) | 985.775) | (82.100) | (84.176) | (84.769) |
| **Inputs' prices** | | | | | | | | | | |
| **Price of labor** | 44.055 | 45.007 | 44.072 | 45.024 | 45.204 | 46.183 | 44.621 | 44.807 | 44.225 | 44.977 |
| **(thousands €)** | (9.109) | (7.467) | (6.832) | (7.793) | (7.376) | (6.539) | (7.407) | (7.964) | (8.904) | (8.055) |
| **Price of capital** | 20.186 | 22.474 | 21.014 | 18.619 | 17.697 | 18.145 | 19.013 | 18.252 | 18.277 | 19.261 |
| **(thousands €)** | (26.076) | (25.137) | (23.209) | (20.420) | (19.656) | (19.788) | (19.310) | (15.930) | (15.758) | (16.642) |
| **Price of other inputs** | 0.448 | 0.463 | 0.472 | 0.491 | 0.512 | 0.576 | 0.567 | 0.580 | 0.583 | 0.609 |
| **(thousands €)** | (0.180) | (0.180) | (0.165) | (0.165) | (0.210) | (0.259) | (0.228) | (0.218) | (0.264) | (0.276) |
| **Airport characteristics** | | | | | | | | | | |
| **Number of runways** | 1.48 | 1.48 | 1.48 | 1.48 | 1.48 | 1.48 | 1.48 | 1.48 | 1.48 | 1.48 |
| **Terminal area (m2)** | 54913 | 54913 | 54913 | 54913 | 54913 | 54913 | 54913 | 54913 | 54913 | 54913 |
| **Airport characteristics in %** | | | | | | | | | | |
| **International passengers** | 44.6% | 45.4% | 47.5% | 46.7% | 45.5% | 45.8% | 46.0% | 47.4% | 47.6% | 47.5% |
| **Majority public** | 65% | 65% | 65% | 65% | 70% | 65% | 61% | 61% | 57% | 57% |

[21] The first number in each cell is the mean, the one between brackets is the standard error.

Table 5 - List of airports and main characteristics in 2015

| Airport | IATA | Class size | Total costs | Δ 2006-2015 (%) | WLUs | Δ 2006-2015 (%) | Commercial revenues | Δ 2006-2015 (%) | Runways | Terminal (m2) | Int. traffic (%) | P. own. (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Alghero | AHO | LRA | €14,412,526 | 7.8% | 1,676,622 | 56.0% | €3,349,341 | 72.1% | 1 | 17,000 | 32.6% | 100% |
| Ancona | AOI | SRA | €12,817,205 | -22.4% | 585,793 | 11.8% | €704,386 | -88.4% | 1 | 15,450 | 61.1% | 99% |
| Bergamo | BGY | LCA | €83,950,805 | 52.0% | 11,514,488 | 73.9% | €27,718,025 | 69.9% | 2 | 34,150 | 69.5% | 40% |
| Bologna | BLQ | NAA | €52,760,549 | 35.7% | 7,166,219 | 73.2% | €28,859,330 | 41.4% | 1 | 44,000 | 75.2% | 86% |
| Cagliari | CAG | LRA | €25,845,744 | -5.0% | 3,748,592 | 49.2% | €4,899,405 | 14.3% | 1 | 41,025 | 19.9% | 95% |
| Catania | CTA | NAA | €47,002,550 | -2.5% | 7,090,302 | 29.9% | €9,038,156 | 23.5% | 1 | 43,110 | 30.0% | 100% |
| Florence | FLR | LRA | €36,324,715 | 53.0% | 2,366,054 | 55.4% | €7,125,393 | 18.4% | 1 | 7,550 | 83.7% | 32% |
| Genova | GOA | LRA | €19,218,660 | 8.1% | 1,356,353 | 24.9% | €6,716,863 | -6.1% | 1 | 12,550 | 42.8% | 85% |
| Lamezia | SUF | LRA | €20,916,179 | 54.1% | 2,346,186 | 72.0% | €4,302,543 | 52.5% | 1 | 15,700 | 18.1% | 68% |
| Lampedusa | LMP | SRA | €1,799,270 | 58.7% | 184,973 | -6.2% | €435,577 | 46.3% | 1 | 1,300 | 0% | 100% |
| Milan | LINMXP | LCA | €453,978,148 | 47.1% | 33,352,591 | -6.8% | €186,486,864 | -9.2% | 4 | 364,765 | 73.1% | 56% |
| Napoli | NAP | NAA | €56,111,346 | 95.0% | 6,203,397 | 21.5% | €20,123,759 | 44.1% | 1 | 30,700 | 60.6% | 25% |
| Olbia | OLB | LRA | €21,322,076 | -18.2% | 2,215,196 | 24.9% | €7,914,234 | -9.0% | 1 | 43,800 | 43.7% | 20% |
| Palermo | PMO | LRA | €50,044,390 | 48.7% | 4,907,025 | 14.2% | €10,003,370 | -1.9% | 2 | 35,400 | 20.4% | 99% |
| Pantelleria | PNL | SRA | €1,238,239 | -4.7% | 131,274 | -14.3% | €268,264 | 3.3% | 1 | 1,600 | 0% | 13% |
| Pescara | PSR | SRA | €8,787,852 | 24.3% | 600,071 | 66.0% | €1,223,312 | 14.5% | 1 | 11,150 | 53.7% | 100% |
| Pisa | PSA | LRA | €60,903,611 | 71.3% | 4,878,574 | 56.6% | €14,479,279 | 13.6% | 2 | 48,942 | 69.7% | 32% |
| Rome | FCOCIA | LCA | €665,425,791 | 35.8% | 47,665,051 | 30.4% | €165,501,529 | -28.9% | 5 | 339,150 | 72.2% | 4% |
| Torino | TRN | LRA | €39,564,109 | -6.7% | 3,666,602 | 12.8% | €14,478,224 | -30.8% | 1 | 58,150 | 49.0% | 23% |
| Trapani | TPS | LRA | €14,285,811 | 290.1% | 1,586,288 | 404.3% | €1,898,256 | 482.7% | 1 | 9,500 | 24.6% | 61% |
| Treviso | TFS | LRA | €18,700,975 | 37.8% | 2,358,222 | 54.8% | €3,311,895 | 86.1% | 1 | 11,500 | 67.5% | 8% |
| Trieste | TRS | SRA | €13,627,824 | 15.2% | 740,419 | 10.5% | €1,939,943 | 9.3% | 1 | 23,505 | 37.8% | 100% |
| Venice | VCE | NAA | €77,462,770 | 26.3% | 9,110,975 | 41.5% | €28,202,640 | 11.8% | 2 | 53,000 | 86.0% | 10% |
| Average | | | €78,108,745 | 36.1% | 6,758,751 | 25.5% | €23,868,721 | -9.7% | 1.5 | 54,913 | 64.0% | 59.0% |

# 5 Results

In performing our analysis, we used the statistical software STATA. The software allows for quick model estimations, therefore it was possible to run the analysis using different specifications with regard to variable selection, functional form and the inefficiency term. In doing so, both models that treated inefficiency as time invariant and models with time-varying inefficiency were used. All models make use of random effects, since the measures of terminal size and number of runways would otherwise be discarded if fixed-effects were used.

A limitation that emerged right away was the difficulty of estimating the cost frontier. In fact, the high correlation between parameters and the size of the dataset required to do a lot of tweaking, as the estimating methods often did not converge when some relevant variables were included. This forced us to make some compromises, starting from the functional form, which was changed to a Cobb-Douglas because the high number of parameters needed to estimate a translog function was problematic. The cost frontier can therefore be expressed as:

$$\ln \hat{C}_{it} = \alpha + \sum_j \beta_j \ln Y_{jit} + \sum_j \varphi_j \ln W_{jit} + \sum_j \gamma_j \ln K_{jit} + \sum_j \tau_j t_j + v_{it} + u_{it}$$

with $\boldsymbol{Y}$ being a vector of outputs, $\boldsymbol{W}$ a vector of input prices, $\boldsymbol{K}$ a vector of fixed capital inputs, $t_j$ a time dummy variable, $v_{it}$ and $u_{it}$ the noise and inefficiency terms.

Another problem was caused by the high correlation among the output measures: WLUs, aircraft movements and commercial revenues. When aircraft movements and WLUs were both included, the model behaved erratically. Many studies used both the number of passengers and of aircraft movements to describe respectively landside and airside activities. However, as noted by Abrate and Erbetta (2010), these studies generally use DEA or TFP, which are less sensitive to collinearity problems. Similarly to their experience, the high

Pearson's correlation of these two variables (0.99), forced us to pick one of them.[22] In their study, the dropped variable had been the aircraft movements. We reached the same conclusion after some testing, since WLU was the measure that behaved more consistently (some of the models would not converge when aircraft movements were included).

All data has been centered to improve numerical stability. Since variables are expressed as logarithms, the estimated coefficients can be interpreted as elasticities.
The variable names are to be interpreted as follows:

| | |
|---|---|
| wlu | Work load units |
| cr | Commercial revenues |
| pl | Price of labor |
| pc | Price of capital |
| po | Price of other inputs |
| run | Number of runways |
| term | Terminal area |
| shareint | Percentage of international passengers |
| dpublic | A dummy variable indicating majorly public ownership |
| year | A variable checking for the time effect, with 2006 as reference year. |

[22] This is coherent with the findings of Abrate and Erbetta (2010), which reported a correlation of 0.98.

## 5.1 Time-varying and time-invariant models

In order to start with the smallest set of assumptions, we begun the analysis using time-varying inefficiency specifications. The frontier was estimated according to the Battese and Coelli (1992) and Khumb (1990) models.[23] From now on, we will refer to them as BC92 and Khumb90. The first model assumes the inefficiency term to be distributed following a truncated normal distribution, while Kumb90 specification uses a half normal. Table 5 shows the estimated coefficients with their respective standard errors.

Table 6 - Estimation of time-varying models

| | **BC92** | | **Kumb90** | |
|---|---|---|---|---|
| | tc | | tc | |
| | Coefficient | Std. Err. | Coefficient | Std. Err. |
| Frontier | | | | |
| wlu | 0.206*** | (0.0384) | 0.260*** | (0.0372) |
| cr | 0.0832*** | (0.0192) | 0.0738*** | (0.0188) |
| pl | 0.397*** | (0.0218) | 0.390*** | (0.0216) |
| pc | 0.189*** | (0.0138) | 0.188*** | (0.0136) |
| po | 0.414*** | (0.0194) | 0.422*** | (0.0196) |
| run | 0.110** | (0.0419) | 0.139*** | (0.0342) |
| term | 0.500*** | (0.0614) | 0.426*** | (0.0572) |
| dpublic | -0.0513* | (0.0212) | -0.0395* | (0.0198) |
| shareint | -0.232** | (0.0713) | -0.193** | (0.0668) |
| year=2007 | -0.0929*** | (0.0228) | 0.00155 | (0.0201) |
| year=2008 | -0.235*** | (0.0320) | -0.0412 | (0.0221) |
| year=2009 | -0.356*** | (0.0444) | -0.0596* | (0.0245) |
| year=2010 | -0.491*** | (0.0602) | -0.0859** | (0.0271) |
| year=2011 | -0.643*** | (0.0785) | -0.117*** | (0.0298) |
| year=2012 | -0.787*** | (0.0987) | -0.125*** | (0.0308) |
| year=2013 | -0.982*** | (0.121) | -0.171*** | (0.0306) |
| year=2014 | -1.154*** | (0.147) | -0.177*** | (0.0309) |
| year=2015 | -1.331*** | (0.176) | -0.178*** | (0.0317) |
| Constant | -2.326*** | (0.158) | -0.366*** | (0.0707) |
| $\eta$ | -0.0523 | (0.0261) | | |
| $t$ | | | -0.124 | (0.129) |
| $t^2$ | | | -0.0308 | (0.0273) |
| $\sigma_u$ | 0.348 | | 0.524 | |
| $\sigma_v$ | 0.0638 | | 0.0637 | |
| Observations | 230 | | 230 | |

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[23] Refer to the previous chapter to see how the time variance was expressed in the two models.

Looking at the estimates, the coefficients of outputs and input prices have the expected sign. Both models find all outputs, input prices and not-time-related control variables to be statistically significant. The two specifications lead to estimated coefficients that are similar in the case of input prices, but differ considerably in the case of the *wlu* term and the constant term. Another big difference can be found in the estimated coefficients of the year variables. Overall, the correlation among the inefficiency terms of the two models is 0.727, which implies that an airport which appears to be inefficient in a model is similarly characterized in the other.

The analysis was also performed using Greene (2005) and Cornwell et al. (1990) specifications. Greene's specification lead to unreliable results, uncorrelated with those obtained from the other models. All DMUs were reported as being almost completely efficient, due to the way the model defines the $\boldsymbol{u}$ term. Cornwell's model on the other hand required estimating too many parameters, which is the reason why we had to avoid using the translog functional form in the first place. These estimates are not reported, as they are not relevant.

As the previous table shows, the two time-invariance hypothesis, $H_0 : b = c = 0$ and $H_0 : \eta = 0$, cannot be rejected at the 5% level. This seems to suggest that the economic inefficiency in the Italian airport system is time invariant.[24] To test this hypothesis out, two time-invariant models were used: the Battese and Coelli (1988) and the Pitt and Lee (1981) specifications. From now on, we will refer to them as BC88 and PL81. Both models make use of maximum likelihood estimators. While the first one assumes the inefficiency term to follow a truncated normal, the second assumes a half normal distribution. The results are shown in Table 6.

[24] Such a conclusion is valid only for the timeframe taken into account in the study.

Table 7 - Estimation of time-invariant models

| | **PL81** | | **BC88** | |
|---|---|---|---|---|
| | tc | | tc | |
| | Coefficient | Std. Err. | Coefficient | Std. Err. |
| Frontier | | | | |
| wlu | 0.176*** | (0.0473) | 0.155*** | (0.0461) |
| cr | 0.107*** | (0.0226) | 0.113*** | (0.0229) |
| pl | 0.423*** | (0.0260) | 0.409*** | (0.0260) |
| pc | 0.205*** | (0.0157) | 0.208*** | (0.0155) |
| po | 0.372*** | (0.0212) | 0.382*** | (0.0214) |
| run | 0.270*** | (0.0320) | 0.262*** | (0.0520) |
| term | 0.306*** | (0.0554) | 0.280*** | (0.0539) |
| dpublic | -0.0376 | (0.0248) | -0.0429 | (0.0252) |
| shareint | -0.458*** | (0.0963) | -0.307** | (0.107) |
| year=2007 | 0.0295 | (0.0229) | 0.0296 | (0.0229) |
| year=2008 | 0.0211 | (0.0232) | 0.0172 | (0.0233) |
| year=2009 | 0.0378 | (0.0235) | 0.0357 | (0.0234) |
| year=2010 | 0.0417 | (0.0243) | 0.0430 | (0.0242) |
| year=2011 | 0.0443 | (0.0251) | 0.0452 | (0.0250) |
| year=2012 | 0.0607* | (0.0255) | 0.0606* | (0.0254) |
| year=2013 | 0.0369 | (0.0259) | 0.0346 | (0.0258) |
| year=2014 | 0.0442 | (0.0266) | 0.0422 | (0.0265) |
| year=2015 | 0.0522 | (0.0275) | 0.0509 | (0.0274) |
| Constant | -0.631*** | (0.0875) | -0.824*** | (0.172) |
| $\sigma_u$ | 0.328 | | 0.176 | |
| $\sigma_v$ | 0.0765 | | 0.0764 | |
| Observations | 230 | | 230 | |

Standard errors in parentheses
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Coefficient estimates of outputs and input prices are all significant and have the expected signs. The two models give similar estimates, with the exception of *shareint* and the constant term. All year dummy variables are not statistically significant, aside from the one for the year 2012. The same is true for *dpublic*. These two are the most evident differences with the time-varying models, although the coefficient estimates are quite different overall. The exception is the input prices estimation, which leads to similar results in the four specifications. The signal to noise ratio $\sigma_u/\sigma_v$ is neither too large nor too small in the four models taken into account. This is a good sign, as a preponderance of one of the two terms can lead to numerical maximization problems. The $\boldsymbol{u}$ terms of the PL81 and BC88 models are strongly correlated, with a value of 0.959. The two models lead to similar results, which are reported in Table 7.

Table 8 – A comparison of the efficiency estimates of PL81 and BC88 models

| **Airport** | **IATA** | **PL81** | **BC88** |
|---|---|---|---|
| Alghero | AHO | 67.3% | 60.8% |
| Ancona | AOI | 75.6% | 72.3% |
| Bergamo | BGY | 64.5% | 58.7% |
| Bologna | BLQ | 59.7% | 54.3% |
| Cagliari | CAG | 94.6% | 79.9% |
| Catania | CTA | 84.2% | 70.5% |
| Florence | FLR | 46.7% | 46.1% |
| Genova | GOA | 66.3% | 60.7% |
| Lamezia | SUF | 69.9% | 61.0% |
| Lampedusa | LMP | 89.3% | 82.1% |
| Milan | LINMXP | 74.7% | 61.3% |
| Napoli | NAP | 64.8% | 57.8% |
| Olbia | OLB | 96.7% | 85.6% |
| Palermo | PMO | 85.2% | 71.2% |
| Pantelleria | PNL | 71.0% | 65.6% |
| Pescara | PSR | 98.3% | 96.1% |
| Pisa | PSA | 73.0% | 66.3% |
| Rome | FCOCIA | 96.0% | 78.3% |
| Torino | TRN | 89.2% | 77.9% |
| Trapani | TPS | 74.4% | 66.7% |
| Treviso | TFS | 68.0% | 66.1% |
| Trieste | TRS | 94.4% | 85.5% |
| Venice | VCE | 76.2% | 68.9% |

The efficiency scores estimated with the BC88 model tend to be lower than their PL81 counterpart, though their order does not change substantially. We chose PL81 as the reference model since we felt that its more conservative estimates of the inefficiency term were a safer choice, and lead to less drastic conclusions. We remind that in these models all time-invariant unobserved heterogeneity is considered as inefficiency. An incomplete model specification may therefore be the reason behind some unexpectedly low scores, like in the case of Florence airport.

## 5.2 Time-invariant model with PCA

As previously stated, a recurrent problem in the analysis was caused by the multicollinearity of the regressors. The following table reports the correlation among the variables we used.

Table 9 - Correlation among regressors

| | wlu | mov | cr | pl | pc | po | run | term | dpublic | shareint |
|---|---|---|---|---|---|---|---|---|---|---|
| wlu | 1 | | | | | | | | | |
| mov | 0.976 | 1 | | | | | | | | |
| cr | 0.958 | 0.969 | 1 | | | | | | | |
| pl | 0.617 | 0.608 | 0.654 | 1 | | | | | | |
| pc | 0.851 | 0.851 | 0.853 | 0.698 | 1 | | | | | |
| po | 0.425 | 0.331 | 0.408 | 0.490 | 0.468 | 1 | | | | |
| run | 0.709 | 0.754 | 0.719 | 0.292 | 0.456 | 0.199 | 1 | | | |
| term | 0.907 | 0.905 | 0.897 | 0.619 | 0.791 | 0.534 | 0.699 | 1 | | |
| dpublic | -0.120 | -0.150 | -0.158 | 0.0845 | -0.125 | 0.0605 | -0.145 | -0.025 | 1 | |
| shareint | 0.502 | 0.498 | 0.552 | 0.485 | 0.605 | 0.550 | 0.355 | 0.474 | -0.265 | 1 |

We can see how WLUs, aircraft movements, commercial revenues, terminal area and price of capital are strongly correlated. Collinearity between predictors may cause coefficient estimates to respond erratically to small changes in the model or the data. In our analysis, this lead to the choice of dropping the *mov* variable. Although a sensible choice, it still determines a loss in explanatory power. As a way to tackle this problem, a principal component analysis (PCA) was performed. PCA is a procedure aimed at reducing data dimensionality by a suitable linear transformation. Given the initial variables $X_j, j = 1, \dots, p$, we seek a set of orthogonal linear combinations

$$Z_k = \sum_j^p a_{kj} X_j, \quad k = 1, \dots, q < p$$

that account for most of the observed variability. $Z_k$ are called principal components. The transformation is defined in a way that the first principal component accounts for the largest variability observed in the dataset, and each following one has the largest variance possible under the constraint of being independent from the others.[25]

[25] See Brandimarte (2011) for an in-depth analysis.

No study that we are aware of has combined PCA with SFA, although some examples of PCA with DEA were found. Nevertheless, it is quite common to use PCA with regression analysis to aggregate variables and improve stability.

A drawback of PCA is the loss of economic significance of the new regressors. In fact, being a linear combination of the initial variables, they are not easily interpretable. Therefore, to avoid generating components which aggregated too different measures, we opted to apply PCA only to output measures and a fixed input one. That is: WLUs, aircraft movements, commercial revenues, and terminal area. Although highly correlated, we did not include the price of capital. Since variables have the same order of magnitude, standardization was not required.

Table 10 - PCA results

| Component | Eigenvalue | Difference | Proportion | Cumulative |
|---|---|---|---|---|
| Comp1 | 3.80698 | 3.67867 | 0.9517 | 0.9517 |
| Comp2 | 0.128304 | 0.0851683 | 0.0321 | 0.9838 |
| Comp3 | 0.0431356 | 0.0215517 | 0.0108 | 0.9946 |
| Comp4 | 0.0215839 | . | 0.0054 | 1.0000 |

| Variable | Comp1 | Comp2 | Comp3 | Comp4 | Unexplained |
|---|---|---|---|---|---|
| wlu | 0.5047 | -0.2384 | -0.6194 | 0.5521 | 0 |
| mov | 0.5059 | -0.2876 | -0.1834 | -0.7923 | 0 |
| cr | 0.5023 | -0.3161 | 0.7620 | 0.2591 | 0 |
| term | 0.4868 | 0.8721 | 0.0464 | -0.0164 | 0 |

Table 9 shows the results of the principal component analysis. The first two principal components found explain 98.38% of the dataset variability. We can estimate the model with these alone, as the loss of information in excluding the other two is minimal. The estimation was again performed using the Pitt and Lee model. The results are shown in Table 10.

Table 11 - Estimation with PCA generated regressors

| | **PL_PCA** | |
|---|---|---|
| | tc | |
| | Coefficient | Std. Err. |
| Frontier | | |
| comp1 | $0.420^{***}$ | (0.0180) |
| comp2 | $0.111^{*}$ | (0.0535) |
| pl | $0.411^{***}$ | (0.0238) |
| pc | $0.194^{***}$ | (0.0145) |
| po | $0.395^{***}$ | (0.0197) |
| run | $0.232^{***}$ | (0.0252) |
| dpublic | -0.0372 | (0.0228) |
| shareint | $-0.413^{***}$ | (0.0737) |
| year=2007 | 0.0215 | (0.0217) |
| year=2008 | 0.0165 | (0.0220) |
| year=2009 | 0.0341 | (0.0219) |
| year=2010 | 0.0393 | (0.0222) |
| year=2011 | $0.0439^{*}$ | (0.0224) |
| year=2012 | $0.0586^{**}$ | (0.0227) |
| year=2013 | 0.0399 | (0.0226) |
| year=2014 | $0.0513^{*}$ | (0.0226) |
| year=2015 | $0.0596^{**}$ | (0.0228) |
| Constant | $-1.106^{***}$ | (0.0579) |
| $\sigma_u$ | 0.264 | |
| $\sigma_v$ | 0.0726 | |
| Observations | 230 | |

Standard errors in parentheses
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Clearly, the output measures and the *term* variable are now excluded from the model, so their coefficients cannot be estimated. The two regressors *comp1* and *comp2* have no clear economic meaning. Nevertheless, being the principal components linearly uncorrelated, the estimation of the remaining coefficients and of the inefficiency term is more precise. The first thing to be noted is that the estimation of the prices of inputs are very similar to PL81. The dummy variable *dpublic* is again nonsignificant, while some time dummy variables are now statistically significant (it was only the one for year 2012 in PL81). With *sharint* having a similar value, the only substantial difference lays in the estimate of the constant term.

Table 12 - Correlation of inefficiency estimates.

| | upl81 | uplpca | ubc88 | ubc92 | ukumb90 |
|---|---|---|---|---|---|
| upl81 | 1 | | | | |
| uplpca | 0.984 | 1 | | | |
| ubc88 | 0.959 | 0.948 | 1 | | |
| ubc92 | 0.366 | 0.349 | 0.323 | 1 | |
| ukumb90 | 0.644 | 0.616 | 0.564 | 0.727 | 1 |

Table 11 shows how the Pitt and Lee with and without principal components and the BC88 models result in strongly correlated inefficiency estimates. This finding bolster the idea that the models are well specified.

Table 13 - A comparison of the efficiency estimates of PL81 and PL_PCA models

| **Airport** | **IATA** | **PL81** | **PL_PCA** |
|---|---|---|---|
| Alghero | AHO | 67.3% | 68.9% |
| Ancona | AOI | 75.6% | 79.6% |
| Bergamo | BGY | 64.5% | 71.4% |
| Bologna | BLQ | 59.7% | 66.9% |
| Cagliari | CAG | 94.6% | 96.9% |
| Catania | CTA | 84.2% | 91.0% |
| Florence | FLR | 46.7% | 55.8% |
| Genova | GOA | 66.3% | 71.2% |
| Lamezia | SUF | 69.9% | 72.0% |
| Lampedusa | LMP | 89.3% | 94.5% |
| Milan | LINMXP | 74.7% | 76.1% |
| Napoli | NAP | 64.8% | 72.4% |
| Olbia | OLB | 96.7% | 96.2% |
| Palermo | PMO | 85.2% | 89.5% |
| Pantelleria | PNL | 71.0% | 77.6% |
| Pescara | PSR | 98.3% | 98.5% |
| Pisa | PSA | 73.0% | 75.5% |
| Rome | FCOCIA | 96.0% | 96.4% |
| Torino | TRN | 89.2% | 93.6% |
| Trapani | TPS | 74.4% | 76.7% |
| Treviso | TFS | 68.0% | 72.7% |
| Trieste | TRS | 94.4% | 94.5% |
| Venice | VCE | 76.2% | 83.4% |

We can see how the efficiency estimates do not change substantially in the two models, save for a few exceptions (e.g. Florence, which gains +9%). This translates in an ordering that is extremely similar for the two specifications. These facts, together with the high correlation indices of the $\boldsymbol{u}$ term for PL81, BC88 and PT_PCA and the similar coefficient estimates make us confident on the robustness of the model.

## 5.3 Dealing with outliers

Table 14 - Excerpt of summary statistics of the dataset for the year 2015

| Airport | Class size | Total costs | WLUs | Commercial revenues | Terminal area |
|---|---|---|---|---|---|
| Rome | LCA | €665,425,790.91 | 47665051 | €165,501,529.44 | 339150 |
| Milan | LCA | €453,978,147.92 | 33352591 | €186,486,863.61 | 364765 |
| Bergamo | LCA | €83,950,805.43 | 11514488 | €27,718,024.69 | 34150 |
| Venice | NAA | €77,462,769.75 | 9110975 | €28,202,639.85 | 53000 |
| Pisa | LRA | €60,903,610.76 | 4878574 | €14,479,279.28 | 48942 |
| Napoli | NAA | €56,111,345.86 | 6203397 | €20,123,758.64 | 30700 |
| Bologna | NAA | €52,760,548.92 | 7166219 | €28,859,330.12 | 44000 |
| Trieste | SRA | €13,627,824.47 | 740419 | €1,939,942.70 | 23505 |
| Ancona | SRA | €12,817,204.73 | 585793 | €704,385.88 | 15450 |
| Pescara | SRA | €8,787,852.21 | 600071 | €1,223,311.84 | 11150 |
| Lampedusa | SRA | €1,799,270.35 | 184973 | €435,576.68 | 1300 |
| Pantelleria | SRA | €1,238,238.65 | 131274 | €268,263.52 | 1600 |

Table 13 presents some relevant statistics regarding the airports that compose our dataset. Observations were sorted by WLU, and only the top 7 and last 5 of the dataset for year 2015 are reported. What is immediately striking is the enormous difference between the top and bottom observations. Although this reflects the heterogeneous nature of the Italian airport system, it begs the question if some of these observations should in fact be treated as outliers. We therefore estimated three frontiers excluding some of these airports from the dataset: Rome and Milan (NRM model), Pantelleria and Lampedusa (NPL model), and all four airports (NRMPL model). The findings are shown in Table 14.

Table 15 - Estimation excluding outliers

| | **NRM** | | **NPL** | | **NRMPL** | |
|---|---|---|---|---|---|---|
| | tc | | tc | | tc | |
| | Coefficient | Std. Err. | Coefficient | Std. Err. | Coefficient | Std. Err. |
| Frontier | | | | | | |
| wlu | 0.165** | (0.0512) | 0.414*** | (0.0428) | 0.431*** | (0.0448) |
| cr | 0.104*** | (0.0239) | 0.0392* | (0.0191) | 0.0291 | (0.0195) |
| pl | 0.427*** | (0.0269) | 0.354*** | (0.0244) | 0.357*** | (0.0251) |
| pc | 0.204*** | (0.0164) | 0.170*** | (0.0137) | 0.163*** | (0.0142) |
| po | 0.368*** | (0.0226) | 0.476*** | (0.0208) | 0.479*** | (0.0221) |
| run | 0.425*** | (0.0850) | 0.243*** | (0.0354) | 0.299*** | (0.0537) |
| term | 0.319*** | (0.0584) | 0.178** | (0.0598) | 0.183** | (0.0616) |
| dpublic | -0.0425 | (0.0260) | -0.0444* | (0.0201) | -0.0439* | (0.0201) |
| shareint | -0.420*** | (0.0984) | -0.392*** | (0.0830) | -0.360*** | (0.0818) |
| year=2007 | 0.0317 | (0.0244) | 0.0151 | (0.0184) | 0.0153 | (0.0193) |
| year=2008 | 0.0233 | (0.0247) | 0.00125 | (0.0187) | 0.00203 | (0.0196) |
| year=2009 | 0.0437 | (0.0250) | -0.0167 | (0.0191) | -0.0175 | (0.0202) |
| year=2010 | 0.0482 | (0.0260) | -0.0289 | (0.0202) | -0.0305 | (0.0214) |
| year=2011 | 0.0498 | (0.0269) | -0.0570** | (0.0218) | -0.0618** | (0.0230) |
| year=2012 | 0.0730** | (0.0273) | -0.0489* | (0.0222) | -0.0471* | (0.0236) |
| year=2013 | 0.0498 | (0.0276) | -0.0715** | (0.0227) | -0.0668** | (0.0240) |
| year=2014 | 0.0537 | (0.0283) | -0.0859*** | (0.0236) | -0.0842*** | (0.0247) |
| year=2015 | 0.0569 | (0.0292) | -0.0814** | (0.0248) | -0.0838** | (0.0258) |
| Constant | -0.827*** | (0.158) | -0.497*** | (0.0728) | -0.569*** | (0.0926) |
| $\sigma_u$ | 0.330 | | 0.283 | | 0.287 | |
| $\sigma_v$ | 0.0778 | | 0.0584 | | 0.0583 | |
| Observations | 210 | | 210 | | 190 | |

Standard errors in parentheses
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

We can see how the estimated coefficients do not change substantially when excluding Rome and Milan from the analysis. On the other hand, the exclusion of Pantelleria and Lampedusa airports leads to completely different estimates. The elasticity of cost with respect to *wlu* increases considerably, going from 0.176 to 0.414. The opposite happens for *cr*, which from 0.107 goes to 0.039. Estimates of prices of inputs are less strongly affected, but still noticeably different. Although only at the 5% level, *dpublic* becomes significant. This is also the case for the time dummy variables from 2011 onwards, which also register a change in sign from positive to negative, which is the expected relation with costs as it implies an increased efficiency as time goes on. The third frontier, NRMPL, does not differ much from the second. However, a significant difference lies in the estimated coefficient of *cr*, which becomes nonsignificant. We will return to this on the next subchapter.

Table 16 - A comparison of the efficiency estimates with and without outliers

| **Airport** | **IATA** | **PL81** | **NPL** |
|---|---|---|---|
| Alghero | AHO | 67.3% | 74.7% |
| Ancona | AOI | 75.6% | 67.0% |
| Bergamo | BGY | 64.5% | 80.4% |
| Bologna | BLQ | 59.7% | 61.9% |
| Cagliari | CAG | 94.6% | 98.0% |
| Catania | CTA | 84.2% | 93.1% |
| Florence | FLR | 46.7% | 51.9% |
| Genova | GOA | 66.3% | 64.5% |
| Lamezia | SUF | 69.9% | 77.2% |
| Milan | LINMXP | 74.7% | 74.9% |
| Napoli | NAP | 64.8% | 71.3% |
| Olbia | OLB | 96.7% | 90.9% |
| Palermo | PMO | 85.2% | 91.9% |
| Pescara | PSR | 98.3% | 98.3% |
| Pisa | PSA | 73.0% | 77.0% |
| Rome | FCOCIA | 96.0% | 96.8% |
| Torino | TRN | 89.2% | 81.2% |
| Trapani | TPS | 74.4% | 80.7% |
| Treviso | TFS | 68.0% | 84.9% |
| Trieste | TRS | 94.4% | 86.7% |
| Venice | VCE | 76.2% | 81.5% |

As Table 15 shows, some airports report a substantial change in their efficiency estimate when excluding the airports of Pantelleria and Lampedusa, and an overall increase in average efficiency is registered, from 77.4% to 80.2%. The big effect that dropping these two DMUs has on the estimated frontier, and the small relevance the two insular airports have in relative terms (together, they account for 0.17% of the dataset total costs and 0.20% of WLUs) made us deem appropriate to exclude Pantelleria and Lampedusa airports from the dataset.

From the results of the analysis, returns to scale (RTS) can be calculated as:

$$RTS = \frac{1}{\sum_i \frac{\partial C}{\partial Y_i}\frac{Y_i}{C}} = \frac{1}{\sum_i \eta_i}$$

with $\eta_i$ being the elasticity of cost with respect to output $Y_i$. In our case, this would lead to an estimated RTS of 2.21. This number is extremely high, and does not seem reasonable from an economic point of view. An explanation to this comes from the chosen functional form. In fact, a downside of the Cobb-Douglas functional form is that the estimated returns to scale do not change with the volume of output. This therefore leads to inaccurate results, so that we leave it to future studies that make use of a flexible functional form to better examine returns to scale for the Italian airports.

## 5.4 Subgroup analysis

Although not as dramatic as the effect caused by the exclusion of Pantelleria and Lampedusa, the omission of Rome and Milan in the NPLRM model did lead to the influence of commercial revenues on costs to become statistically nonsignificant. This is an interesting finding; however, the exclusion of the airports of Rome and Milan from the dataset would be too drastic a measure, as they account for 62% of the dataset total costs and 52% of WLUs. On the other hand, this could imply that it is not appropriate to try to calculate a single cost function for all the airports since they differ greatly.

To assess if substantial differences exist between large airports and small ones, a frontier analysis was performed dividing the dataset into two subgroups: The first one composed by airports having more than 5 million passengers per year (LCA and NAA class sizes), the second one made up of the remaining others (LRA and SRA). We therefore estimated two separate frontiers, whose results are shown in Table 16.

Table 17 - Estimation within subgroups[26]

| | **Large Airports** | | **Small Airports** | |
|---|---|---|---|---|
| | tc | | tc | |
| | Coefficient | Std. Err. | Coefficient | Std. Err. |
| Frontier | | | | |
| wlu | 0.396*** | (0.0782) | 0.400*** | (0.0536) |
| cr | 0.164** | (0.0601) | 0.0422 | (0.0219) |
| pl | 0.205*** | (0.0514) | 0.383*** | (0.0292) |
| pc | 0.175*** | (0.0276) | 0.161*** | (0.0168) |
| po | 0.620*** | (0.0433) | 0.456*** | (0.0252) |
| run | -0.0397 | (0.0779) | 0.296*** | (0.0693) |
| term | 0.400*** | (0.117) | 0.165* | (0.0748) |
| dpublic | -0.0893* | (0.0351) | -0.0463 | (0.0249) |
| shareint | -0.0300 | (0.0972) | -0.469*** | (0.104) |
| year=2007 | -0.00423 | (0.0254) | 0.0188 | (0.0239) |
| year=2008 | -0.0472 | (0.0275) | 0.00827 | (0.0242) |
| year=2009 | -0.0923** | (0.0282) | 0.00700 | (0.0250) |
| year=2010 | -0.0997** | (0.0304) | -0.00724 | (0.0265) |
| year=2011 | -0.136*** | (0.0336) | -0.0361 | (0.0284) |
| year=2012 | -0.145*** | (0.0329) | -0.0200 | (0.0292) |
| year=2013 | -0.199*** | (0.0358) | -0.0360 | (0.0295) |
| year=2014 | -0.207*** | (0.0400) | -0.0600* | (0.0301) |

[26] The analysis was also repeated with the inclusion of Pantelleria and Lampedusa to the small airport subgroup, but this led to unreliable coefficients estimation. We chose not to present for simplicity's sake.

| | | | | |
|---|---|---|---|---|
| year=2015 | -0.206*** | (0.0458) | -0.0662* | (0.0317) |
| Constant | 0.105 | (0.134) | -0.574*** | (0.120) |
| $\sigma_u$ | 0.0880 | | 0.294 | |
| $\sigma_v$ | 0.0441 | | 0.0613 | |
| Observations | 70 | | 140 | |

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In both cases, the output coefficients imply positive marginal costs, and total costs increase with input prices. The two estimations suggest that there are some relevant differences in the cost structure of large and small airports. In the small airports subgroup, $cr$ becomes statistically nonsignificant. This is the first important divergence between the two models, and it is understandable from an economic viewpoint since commercial revenues are strongly dependent on the number of passengers that an airport attracts. The low number of passengers causes non-aviation activities to become not relevant. On the other hand, the elasticity of cost with respect to *cr* for the large airports subgroup increases considerably, from 0.039 of the pooled data to 0.164.

Another important difference is given by the estimates of input prices, which change completely. While in the case of small airports they are quite similar to the pooled estimates, for large airports the price of labor has a much lower impact on costs, and the coefficient of the price of other inputs registers instead a 30% increase.

In the case of large airports, the ownership structure becomes statistically significant, although only at the 5% level. Finally, it is important to notice how the time dummy variables behave in the two models. If for small airports they are mostly nonsignificant, large airports have decreasing costs in relation to time which become statistically significant starting from the year 2009. This should come as no surprise: From 2009 the airports that had signed a programme contract with ENAC got their charges adjusted to actual costs sustained, while the other airport operators' charges were adjusted only to inflation.[27] The operators that signed these contracts mostly belonged to LCA and NAA class sizes.

[27] Refer to Keller and Galli (2014).

Table 18 - A comparison of the efficiency estimates using pooled data and vs subgroups

| **Airport class** | **Average efficiency** | | **Correlation of u** |
|---|---|---|---|
| | **Pooled** | **Subgroup** | |
| Large airports (LCA and NAA) | 0.743 | 0.933 | 0.871 |
| Small airports (LRA and SRA) | 0.786 | 0.772 | 0.960 |

As Table 17 shows, differences in efficiency across groups are greater when we estimate two frontiers. With pooled data, the mean level of efficiency is 0.743 for large airports and 0.786 for small ones. When separate frontiers are derived, the mean level of efficiency is 0.933 and 0.722, respectively. Pooled data therefore tends to underestimate considerably the efficiency levels of larger airports. However, as pointed out by Zuckerman et al. (1994), when efficiency is measured based on separate frontiers, the results cannot be compared across groups, since each subgroup uses its own frontier as reference point.
In both cases, the $\boldsymbol{u}$ term is strongly correlated with the pooled result. This implies that an airport which appears to be inefficient relative to other airports based on the pooled frontier will be similarly characterized by a group-specific frontier.

Although the use of different frontiers offers new insights, it could be argued that the division in two subgroups is quite arbitrary, and that estimating four frontiers, one for each class size, would have been a better choice. Such a conclusion may well be true, since the differences between SRA and LRA or LCA and NAA are considerable. However, a limitation is again imposed by the size of the dataset. In the last estimation, the large airport subgroup had only 70 observations, which is sufficient but on the low side to estimate 20 parameters. Dividing the dataset into further subgroups would cause the estimation to be unfeasible (e.g. a LCA subgroup would have only 30 observations).

# 6 Conclusions

In this work we have provided a methodological framework for the evaluation of the economic efficiency of Italian airports. Our analysis was based on a stochastic Cobb-Douglas cost frontier model, with a dataset of 23 Italian airports for the period 2006-2015.
We found strong evidence that there is a significant margin of improvement for airport operators, since the average efficiency is roughly 80%. This finding is consistent with previous studies, like the one by Abrate and Erbetta (2010), although relative to a different timeframe. We identified the main drivers of economic efficiency in the industry to be number of WLUs, price of labor and of other inputs, and the percentage of international passenger traffic.
The estimation of two separated cost frontiers showed how large and small airports have a substantially different cost structure. LCA and NAA airports have a much lower elasticity of cost with respect to labor price, and commercial revenues and terminal size have a much stronger impact on cost.
Percentage of international passenger traffic appears to be a main driver of cost reduction for small airports, while it does not seem to be relevant for large airports.
Interestingly, in the case of large airports, a cost reduction effect associated with majorly public ownership was found, albeit small. The literature is quite murky in this regard, since different authors have reported both negative and positive effects of public ownership of airports with regard to economic efficiency. Given the really small impact, this finding suggests that the competitive environment pushes airport operators to operate efficiently, regardless of the ownership structure. Although the time period of the analysis was of 10 years, only large airports showed a significant increase in efficiency in relation to time. For small airports, technical change did not contribute to a reduction of costs.
No statistically significant relation was found between costs and percentage of low cost passenger traffic, although such a connection was expected since the presence of low cost carriers is usually associated with an increase in competitive pressure, which leads to a higher economic efficiency.

The sample size and the difficulty of finding relevant data were the main difficulties encountered in our work. Further research, performed with a larger dataset, could try to address the limitations faced in the present analysis.

# 7 References


Abrate, G., and F. Erbetta. 2010. "Efficiency and patterns of service mix in airport companies: an input distsance function approach." *Transportation Research Part E 46* 693–708.

Aigner, D., K. Lovell, and P. Schmidt. 1977. "Formulation and estimation of stochastic frontier function models." *Journal of Econometrics 6* 21-37.

Airports Council International. 2012. *Guide to Airport Performance Measures.* Montreal: ACI.

Barros, C.P. 2008a. " Technical efficiency of UK airports." *Journal of Air Transport Management 14* 175-178.

Barros, C.P. 2008b. "Technical change and productivity growth in airports: a case study." *Transportation Research Part A 42* 818–832.

Barros, C.P., and P.U.C. Dieke. 2008. "Measuring the economic efficiency of airports: A Simar–Wilson methodology analysis." *Transportation Research Part E 44* 1039–1051.

Battese, G. E., and T.J. Coelli. 1988. "Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data." *Journal of econometrics* 38 (3): 387-399.

Battese, G.E., and T.J. Coelli. 1992. "Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India." *Journal of productivity analysis* 3 (1-2): 153-169.

Bel, G., and X. Fageda. 2009. "Privatization, regulation and airport pricing: an empirical analysis for Europe." *Journal of Regulatory Economics, 37* 142-161.

Belotti, F., S. Daidone, G. Ilardi, and V. Atella. 2013. "Stochastic frontier analysis using Stata." *The Stata Journal 13 (4)* 719–758.

Bilotkach, V., J.A. Clougherty, J. Mueller, and A. Zhang. 2012. "Regulation, privatization, and airport charges: panel data evidence from European airports." *Journal of Regulatory Economics 42 (1)* 73-94.

Brandimarte, P. 2011. *Quantitative methods: An introduction for business management.* New York: John Wiley & Sons.

CDP, Cassa Depositi e Prestiti. 2015. "Il sistema aeroportuale italiano."

Christensen, L.R., D.W. Jorgenson, and L.J. Lau. 1973. "Transcendental logarithmic production frontiers." *The review of economics and statistics* 55 (1): 28-45.

Cornwell, C., P. Schmidt, and Sickles R.C. 1990. "Production frontiers with cross-sectional and time-series variation in efficiency levels." *Journal of Econometrics 46 1-2* 185-200.

Craig, S. G., J. Airola, and M. Tipu. 2005. "The effect of institutional form on airport governance efficiency."

Curi, C., S. Gitto, and P. Mancuso. 2011. "New evidence on the efficiency of Italian airports: a bootstrapped DEA analysis." *Socio-Economic Planning Sciences* 45 (2): 84-93.

Curi, C., S. Gitto, and P. Mancuso. 2010. "The Italian airport industry in transition: a performance analysis." *Journal of Air Transport Management 16* 218–221.

Czerny, A.I. 2006. "Price-cap regulation of airports: Single-till versus dual-till." *Journal of Regulatory Economics 30* 85-97.

Elliott, D. 2015. "Setting Airport Regulated Charges: The Choice between Single-till and Dual-till." *Frontier Economics.*

Europe Airports Council International. 2016. "The ownership of Europe's airports." (ACI Europe).

European Commission. 2016. "Annual Analyses of the EU Air Transport Market 2016." (Mott MacDonald).

Fabbri, D., R. Fazioli, and M. Filippini. 1996. *L'intervento pubblico e l'efficienza possibile.* Bologna: Il Mulino.

Färe, R., S. Grosskopf, and J. Logan. 1985. "The relative performance of publicly-owned and privately-owned electric utilities." *Journal of Public Economics 26 (1)* 89-106.

Farrell, M.J. 1957. "The measurements of productive efficiency." *Journal of Royal Statistical Society, Series A, General 120 (3)* 253–281.

Greene, W. 2005. "Fixed and random effects in stochastic frontier models." *Journal of productivity analysis* 23 (1): 7-32.

ICCSAI - International Center for Competitiveness Studies in the Aviation Industry. 2015. "La Competitività del Trasporto Aereo in Europa - Fact Book."

Jondrow, J., C.K. Lovell, and I.S. Materov. 1982. "On the estimation of technical inefficiency in the stochastic frontier production function model." *Journal of econometrics* 19 (2-3): 233-238.

Keller, S., and F. Galli. 2014. "Il sistema aeroportuale italiano: analisi dell'efficienza." *Tesi di dottorato - Università di Salerno.*

Kumbhakar, S.C. 1990. "Production frontiers, panel data, and time-varying technical inefficiency." *Journal of econometrics 46 1-2* 201-211.

Kumbhakar, S.C., and C.A.K. Lovell. 2000. *Stochastic Frontier Analysis.* Cambridge University Press.

Lee, Y.H., and P. Schmidt. 1993. "A production frontier model with flexible temporal variation in technical efficiency." In *The measurement of productive efficiency: Techniques and applications*, by H.O. Fried, C.A.K. Lovell and S.S. Schmidt, 237-255. New York: Oxford University Press.

Macchiati, A., and D. Piacentino. 2006. *Mercato e politiche pubbliche nell'industria del trasporto aereo.* Bologna: Il Mulino.

Martín, J.C., and C. Román. 2009. "A stochastic frontier analysis to estimate the relative efficiency of Spanish airports." *Journal of Productivity Analysis 31 (3)* 163-176.

Martín-Cejas, R.R. 2005. "Two-step estimation method for translog cost function: an application to Spanish airport networks." *International Journal of Transport Economics 32 (2)* 229-234.

Meeusen, W., and J. Van den Boreck. 1977. " Efficiency estimation from Cobb-Douglas production function with composed error." *International Economic Review 18 (2)* 435-444.

Oum, T.H., J. Yan, and C. Yu. 2008. "Ownership forms matter for airport efficiency: A stochastic frontier investigation of worldwide airports." *Journal of Urban Economics 64 (2)* 422-435.

Pels, E., P. Nijkamp, and P. Rietveld. 2003. "Inefficiencies and scale economies of European airport operations." *Transportation Research Part E 39* 341-361.

Pels, E., P. Nijkamp, and P. Rietveld. 2001. "Relative efficiency of European airports." *Transport Policy 8* 183-192.

Pitt, M.M., and L.F. Lee. 1981. "The measurement and sources of technical inefficiency in the Indonesian weaving industry." *Journal of development economics* 9 (1): 43-64.

Schmidt, P., and R.C. Sickles. 1984. "Production frontiers and panel data." *Journal of Business & Economic Statistics 2 (4)* 367-374.

Starkie, D. 2001. "Reforming UK airport regulation." *Journal of Transport Economics and Policy 35 (1)* 119-135.

Zuckerman, S., J. Hadley, and Iezzoni, L. 1994. "Measuring hospital efficiency with frontier cost functions." *Journal of Health Economics 13* 255-280.