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Motivating air navigation service provider performance

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Abstract

The ownership form of Air Navigation Service Providers varies across countries ranging from state agencies belonging to the Department of Transport, to government-owned corporations, to semi-private firms with for-profit or not-for-profit mandates. This research focusses on the link between the performance of ANSPs and their ownership form. A theoretical economic model suggests that effort to achieve cost efficiency will be higher in the case of public companies with a board of stakeholders composed of airspace users and in the case of private companies in which stakeholders are also shareholders. A stochastic frontier analysis estimation of the production and cost functions of 37 European air navigation service providers over nine years suggests that the public-private ownership form achieves statistically significantly higher cost and productive efficiency levels compared to either a government corporation or a state agency.

1. Introduction

Air traffic control provision is one of the last elements of the aviation supply chain to be considered for liberalization. In the United States, where the Federal Aviation Agency serves the entire market as a single government agency, there has been a long discussion as to whether there is a need to commercialize or privatize the service (Kettl and Dilulio, 1997; Treanor, 1997). According to Treanor (1997), the FAA was already suffering from aging equipment, poor procurement policies, budget constraints and mismanagement two decades ago. Theoretically, commercialization or privatization may help to soften some of these issues.

In the European Union, over 80% of the state agencies have been transformed into government corporations in an attempt to enable access to financial markets thus solving some of the budget constraint issues (Elias, 2015; Performance Review Unit, 2016). Of additional concern in Europe is the multiple providers that reduce accessibility to economies of scale. The Single European Sky initiative created a legislative framework in which (1) the 37 air navigation service providers (ANSPs) are required to aggregate into nine functional airspace blocks and (2) a pan-European regulator caps charges according to incentive-based pricing rules. According to Adler et al. (2014) and Baumgartner and Finger (2014), the fragmentation of the European service providers, the home bias of each member state for the national provider, the monopolistic nature of some of the air traffic control services, the network component of most services and the split incentives which require the service providers to invest in new technology without enjoying the direct benefits, neither encourage cost nor productive efficiency in Europe.

With respect to airports, Adler and Liebert (2014) analyze the combined impact of ownership form, economic regulation and competition on airport performance using data envelopment analysis. The empirical results comparing a set of European and Australian airports suggest that in the absence of competition, public airports operate less cost efficiently than fully private airports. In a competitive setting, public and fully private airports operate equally efficiently, however private airports set higher aeronautical charges. In an industry in which there is no competition given the current geographical monopoly status of the air navigation service providers (ANSPs), it is unclear whether a public or private ownership form would stimulate innovation and create a more productive sector (Armstrong and Sappington, 2007). On the one hand, private firms with access to financial markets may have greater interest in cost efficiency. However, regulators have easier access to cost information from publicly owned firms, which may be of use if charge regulation is necessary due to potential abuse of monopoly status. Sappington and Stiglitz (1987) focus on the choice of public versus private provision of goods and services as a function of transaction costs. One of their conclusions is that neither public nor private provision can fully resolve incentive problems that arise from imperfect information. Hart et al. (1997) develop a model in which a provider chooses to invest in improving the quality or reducing the costs of a specific service. The results of the model suggest that the case for privatization is stronger when quality-reducing cost reductions may be controlled through contract or competition, when quality improvements are important and when patronage and powerful unions are a problem. Hence, there would seem to be a basis for arguing that there is a relationship between performance and ownership form. In this research, we develop an economic model in order to analyze the ANSP market and the potential impact of moving from a government agency to a more commercialized setting. Next, this model is tested empirically in the European ANSP setting.

Several published papers have analyzed relative cost efficiency of the ANSPs. Two studies commissioned by the Performance Review Unit of the European Union estimated cost functions using stochastic frontier analysis (NERA, 2006; Veronese et al., 2011) but were not able to draw strong conclusions, in part due to a lack of sufficient data over time. In addition, Button and Neiva (2014) and Bilotkach et al. (2015) analyze the European air traffic control market by applying data envelopment analysis and argue that the performance of the ANSPs varies substantially across countries. One possible explanation could be the influence of ownership form and governance on cost efficiency.

The ownership form of ANSPs varies from state agencies belonging to the Department of Transport to government-owned corporations to semi-private firms with for-profit and not-for-profit motivations (Performance Review Unit, 2016). In Europe, the providers located in France, Greece, Cyprus, Turkey, FYR Macedonia and Poland are defined as state bodies, although some claim to have autonomous budgets. The semi-private forms include MUAC (Maastrict Upper Airspace Control), the United Kingdom and Switzerland. NATS, a public-private partnership was created in 2000[1] with the British government owning 49% of the shares and with a board composed today of stakeholders and a private pension fund. Skyguide is a non-profit, joint stock company with the Swiss government holding 99% of the shares, but legally able to reduce this to 51%, and with a board consisting of seven appointed members (Elias, 2015). MUAC began in the 1960s as an international, non-profit organization operated by Eurocontrol that serves the upper airspace of four countries: Belgium, the Netherlands, Luxembourg and North-West Germany. Consequently, MUACs direct customers are the ANSPs that it serves. The remaining majority are defined as government corporations based on the Performance Review Reports.

The econometric approach to productivity and efficiency estimation is concerned with measuring the performance of firms and institutions in converting inputs to outputs. Stochastic frontier analysis (SFA) distinguishes itself from other methods such as total factor productivity indices, data envelopment analysis and ordinary least squares production models, by estimating a parametric function and levels of technical inefficiency (Coelli et al. 2005). A production plan is deemed technically inefficient if a higher level of output is attainable for the given inputs or the observed output level could be produced using fewer inputs. SFA may be applied to either cross-sectional or panel data at the firm level in order to estimate the relationship between inputs and outputs whilst accounting for exogenous factors. The latter may impact the production relationship however the management of the firm in general may have little to no control.

Whilst we test the technical production efficiency of the ANSPs, we also analyze cost efficiency. A firm is deemed cost efficient if it minimizes the total production cost of a given

[1] http://www.nats.aero/about-us/our-history/. Accessed on 31/5/2017.

output, which requires technical efficiency but also a mix of inputs that makes more intensive use of the relatively cheaper variables. We apply Cobb-Douglas functions which assume log-linear relationships between output, inputs and exogenous drivers. The advantage of the Cobb-Douglas specification is its duality property and simplicity. Furthermore, since the estimations of the parameters proved to be statistically significant across all models, there was no requirement to extend the specification to the more flexible translog function. The functions are also useful for on-going research that models the ANSPs within a game theoretic framework (Adler et al., 2017). Due to the existence of panel data and potential externalities, we apply the Battese and Coelli (1995) model, which accounts for potential heteroscedasticity in the decomposed error terms and the estimation of the impact of externalities on the inefficiency distribution. Consequently, the Battese and Coelli model considers environmental variables twice if necessary, namely within the production or cost function and as an explanation for the average level of inefficiencies (Hattori, 2002).

We find systematic and statistically significant differences in productive and cost efficiency among the European ANSPs. Average productive efficiency increases over the period 2006-2014. The differences in efficiency appear to be related to the ownership form: private-public partnerships or stakeholders on boards encourage significantly higher efficiency in production and cost efficiency. This would appear to suggest that state agencies and government corporations attach a much higher weight to national interests than to the airspace users.

Our results are in contrast to the literature to date. Button and McDougall (2006) provide a general overview of the ownership form of a select set of ANSPs and argue that there is no conclusive evidence that any institutional set-up is superior with respect to productivity, service quality, safety or security. However, improvements in cost-effectiveness and performance and a faster implementation of new technologies as a result of access to financial markets are observed. Lewis and Zolin (2004) analyze the institutional arrangements for governance of air navigation services employing a comparative analysis of six nations. The research focusses on whether boards of public organizations act as a proxy for market feedback, but do not draw any conclusions on the impact with respect to efficiency or production. Button and Neiva (2014) apply bootstrap techniques assuming variable returns to scale in order to analyze 36 European air traffic control systems over the period 2002 to 2009. They argue that ANSPs with larger numbers of sectors appear to be more efficient, suggesting that economies of density or scale exist in the European market. They also find that ANSPs which are closely linked to government appear to be relatively more efficient. The counter-intuitive result may arise due to a selection effect, interdependencies between inefficiencies or to the Averch – Johnson effect, which encourages over-investment in capital under rate-of-return regulation.

An additional contribution of this research is that we estimate both production and cost functions separated by en-route and terminal provision. Consequently, we are also able to compare ANSP and country rankings across all four models, which provides additional insight into the air traffic control market. Accounting for environmental variables, including complexity and seasonality, in addition to the influence of ownership structure, enables us to estimate the average inefficiency distribution and the impact on the individual providers too.

The remainder of the paper is organized as follows. In section 2, we develop a theoretic economic model to analyze the link between ANSP performance and ownership form. In section 3, we estimate the costs and production functions for en-route and for terminal air traffic control providers and analyze the level of influence of ownership form on ANSP performance in the European market. Section 4 draws conclusions and an appendix presents the individual cost and production ANSP efficiency results for en-route activities for the 37 ANSPs analyzed.

2. Economic model

In this section, we develop an economic model to understand the possible links between performance, regulation and ownership form. For this analysis, we extend the theoretical model presented in Blondiau et al. (2016) which explains the efficiency efforts of a regulated monopoly as a function of the objective of the monopolist and the regulatory framework in place. We assume that the objective of an ANSP is likely to draw from three underlying interests, namely maximization of consumer surplus (CS) of the airlines (and indirectly passengers) with weight parameter $\gamma_1^{ANSP_i}$, maximization of profits (π^{ANSP_i}) with weight parameter $\gamma_2^{ANSP_i}$ and national interest (NI) with weight parameter $\gamma_3^{ANSP_i}$. National interest represents both the benefits of the union of ANSP personnel in the form of higher wages and more relaxed working conditions and also the national manufacturers of air traffic control equipment in the form of higher profits and employment for the local equipment provider. This leads to the ANSP mixed goal function of firm *i* presented in equation 2.1.

$$Goal^{ANSP_i} = \gamma_1^{ANSP_i} CS + \gamma_2^{ANSP_i} \pi^{ANSP_i} + \gamma_3^{ANSP_i} NI \tag{2.1}$$

In contrast to Blondiau et al. (2016), the weights now also depend on the ownership form of the ANSP. Multiple assumptions are possible including (1) a public company $ANSP_{public}$ which strives for socially optimal decisions such that the sum of consumer and producer surplus are maximized, so setting $\gamma_1^{ANSP_i} = \gamma_2^{ANSP_i}$; $\gamma_3^{ANSP_i} = 0$; (2) a public company that may attach a higher value to NI as a result of lobbying or fraud $\gamma_3^{ANSP_i} > 0$; or (3) a private company $ANSP_{private}$ which could be influenced by the type of shareholders. Depending on the shareholder composition, a higher weight may be placed on consumer surplus $\gamma_1^{ANSP_i} > \gamma_2^{ANSP_i}$, for example were airlines to be represented on the board, or on profit $\gamma_1^{ANSP_i} < \gamma_2^{ANSP_i}$, for example were pension funds to be shareholders. The same argument may also hold true for public companies in which the consumers are represented on the board.

We assume that the average production cost to provide air navigation services can be broken down into three components; (1) a fixed ANSP cost per flight-hour controlled a, (2) an imperfectly observable cost component θ that varies as a function of the complexity and seasonality of the airspace managed and differences in operational practices and (3) an imperfectly observable, cost reduction potential e or (non-negative) efficiency expressed in average costs per flight-hour. This leads to $c(e)$, the ANSP average operating cost per flight-hour controlled as expressed in equation 2.2.

$$c(e) = a + \theta - e \tag{2.2}$$

The ANSP operating costs are expressed in equation 2.3 in which D represents the total number of standardized flights-hours controlled.

$$OC_{ANSP} = D \cdot c(e) = D \cdot (a + \theta - e) \tag{2.3}$$

For the management and personnel of the ANSP, effort e is costly in terms of stress and long hours but such costs are generally not represented in the accounting system. We represent this *subjective cost* as a quadratic function, $SC(e)$, defined in equation 2.4, which means that exerting more effort becomes increasingly costly. We further assume that the costs of expending effort are higher for relatively larger ANSPs, hence we include the demand parameter D (expressed in flight hours controlled) to represent the scale of operations in addition to the positive cost-scaling parameter $\emptyset$:

$$\mathrm{SC}(e) = D \cdot \frac{\emptyset \cdot e^2}{2} \tag{2.4}$$

The ANSP also receives an income, which depends on the regulated charge permitted. Current Single European Skies regulation is influenced by both price-cap (p_{cap}) and cost-plus (p_{cost+}) regulatory approaches. Under cost-plus regulation, the ANSP charges are equal to the total accounting cost divided by traffic served plus a cost mark-up on capital which allows ANSPs to make a small profit. Under a price-cap, charges are determined by expected costs and demand. Cost efficiency incentives are very different in the two systems. In a pure cost-plus system, all costs are covered irrespective such that incentives to exert substantial efforts to reduce costs are low. In a price-cap system, any average cost realization below the price cap becomes a profit at least until the following round of negotiations. Hence we use the general form for price-cap and cost-plus regulation as shown in equation 2.5. The charge depends on the weights given to the two types of regulation and the level of effort also plays a role. We use a static formulation here where the realization of cost of one individual ANSP does not affect the price-cap of that ANSP in the future years. Otherwise there will be strategic behavior by each ANSP and the price-cap will be less efficient because too much effort by one ANSP will have a negative ratchet effect on the price-cap of that ANSP. The price-cap may change gradually over time but is a function of the aggregate performance of the ANSPs in Europe because the change is not individualized per ANSP.

$$p_{charge}(e) = (1 - \mathrm{B})p_{cap} + \mathrm{B}p_{cost+} = (1 - \mathrm{B})\frac{E(total\ cost)}{E(D)} + \mathrm{B}\frac{total\ cost}{D} = \tag{2.5}$$
$$A + Bc(e)$$

In the second line of (2.5), *A* represents the first term that is constant and exogenous because it is the cost and demand expected by the regulator that is used for the price cap, hence only the second term ($Bc(e)$) is influenced by the ANSP directly.

For this analysis, we use two additional assumptions. First, we assume that A and B are set exogenously, this means that the price cap and the mix of price cap and cost plus regulation is given. Second, we assume that the national interest groups prefer the status quo as they were well served in the period prior to the introduction of the European regulation. Assuming national interest was historically the main ANSP incentive, we have set the importance of national interest proportional to the costs of efficiency effort. This reflects the idea that adding consumer surplus incentives and profit incentives in addition to the national interest will require additional efficiency efforts. $\emptyset$ is introduced in order to interpret $\gamma_3^{ANSP_i}$ as a share of the costs in equation 2.6.

$$\gamma_3^{ANPS_i} NI = -\gamma_3^{ANPS_i} SC(e) = -\gamma_3^{ANPS_i} D \frac{\emptyset e^2}{2} \tag{2.6}$$

Applying the two assumptions, we derive the efficiency effort *e* that is optimal from the point of view of the ANSPs, assuming fixed demand $\overline{D}$. By differentiating the objective function 2.7 (derived from 2.1) with respect to efficiency efforts *e* and applying equations 2.5 and 2.6:

$$Goal^{ANSP_i} = \gamma_1^{ANSP_i} CS + \gamma_2^{ANSP_i} \pi^{ANSP_i} + \gamma_3^{ANSP_i} NI \tag{2.7}$$

$$= \gamma_1^{ANSP_i} \overline{D}(p_{max} - p_{charge}) + \gamma_2^{ANSP_i}(\overline{D}\,(p_{charge} - c) - \mathrm{SC}(e)) - \gamma_3^{ANSP_i} SC(e)$$

where the change in consumer surplus equals the difference between the maximum price (p_{cap}) and the price actually set (p_{charge}), and *c* is the average total cost. We note the two-way influence of efforts on profits. On the one hand, they increase profits because of the reduction in total costs in component *c*. On the other hand, they reduce profits because of the subjective cost of personnel and management efforts. Consequently, equation 2.8 estimates optimal ANSP efficiency effort as follows.

$$e^* = \frac{\gamma_2^{ANSP_i} + B(\gamma_1^{ANSP_i} - \gamma_2^{ANSP_i})}{(\gamma_2^{ANSP_i} + \gamma_3^{ANSP_i})\emptyset} \tag{2.8}$$

In summation, the greater the emphasis on consumer surplus and the lower the emphasis on national interests, the more the ANSP is likely to invest in efficiency efforts. Such effort is also tempered by ANSP profit goals, which is dependent on ownership form and revenue regulation simultaneously.

3. Econometric estimation of the cost and production functions of ANSPs

In this section, we conduct an econometric study in which we analyze European ANSP data mainly drawn from the Performance Review Unit’s air traffic management cost-effectiveness reports. Since 1999, Member States have been required to ensure that ANSPs provide information separately prepared in accordance with Generally Accepted Accounting Principles and independently audited. In addition, they are also required to submit limited separation of key revenue, cost and asset items into those for en-route and those for approach and airport activities, also independently audited. In this research the inputs consist of labor, capital and non-staff operating inputs, the outputs consist of total flight hours controlled en-route (IFR hours) and IFR airport movements at terminals. Since a number of exogenous factors may also have an influence on the production process, we consider socio-economic and operational conditions including traffic complexity and seasonality.

We build on earlier literature assessing econometric cost-efficiency benchmarking of the air traffic management market in Europe including Veronese et al. (2011), with earlier contributions by NERA (2006). We extend the previous studies in a number of ways. First, we have collated the latest performance data that has become available since the previous studies but removed the oldest data because of changes in the data collection procedures, thus the dataset spans the years 2006 to 2014 inclusively. Second, we estimate four separate cost and production functions, per en-route and per terminal control. Previous studies estimated a joint cost function for en-route and terminal provision jointly, known as gate-to-gate provision, utilizing an aggregate output measure referred to as 'composite flight hours'. However, the aggregation of en-route flight hours and terminal movements is somewhat artificial and relatively crude[2]. The goal is to reduce potential bias due to variation in boundaries between en-route and terminal activities among ANSPs.

The economic theory underlying the estimation of a cost function relies on the assumption that firms minimize costs subject to the available technologies. However, this may be less relevant for ANSPs because, despite a large majority being corporatized public entities, they are also statutory monopolies and up until 2009 were operating under a full cost recovery regime. The price cap incentive regulation in place since 2010 is set at the European level and appears to suffer from political issues, suggesting that the impact has been weak to date (Baumgartner and Finger, 2014). Therefore, it could be argued that most ANSPs face relatively weak incentives to ensure an efficient use of inputs during the period considered in this analysis.

[2] Most previous econometric productivity benchmarking studies estimate a single cost model and use composite flight hours as the relevant output measure. The "gate-to-gate" perspective was considered preferable because the boundaries used to allocate costs between en-route and terminal services vary across ANSPs and might introduce a bias in the cost-effectiveness analysis. The combined variable was determined by weighting the output measures according to their respective average cost for the Pan-European system. This average weighting factor is based on the total monetary value of the outputs and amounts to 0.27 (Performance Review Commission, 2006). However, Price Waterhouse Coopers (2011) argue that significant bias may exist in the composite flight hour measure due to the existence of cross-subsidization between en-route and terminal control activities. Consequently, the use of the composite measure may put one ANSP at a (dis)advantage, depending on the intensity of activities in en-route and terminal control.

This section is structured as follows. In section 3.1, we present the methodological modelling approach relevant to analyze the air traffic control market. In section 3.2, we discuss the dataset and the approach taken to construct the variables for the cost and production functions. Finally, in section 3.3, we present the results of the estimations.

3.1 Stochastic frontier analysis

The Battese and Coelli (1995) model analyzes panel-data, which accounts for potential heteroscedasticity and includes explanatory variables also in the inefficiency distribution. The Battese and Coelli production model defines inefficiency as in equation 3.1 and output as in equation 3.2. The explanatory variables should be uncorrelated with the error term as they are determined exogenously to the production and cost relationships. The error term is decomposed into a noise term v_{it} and an inefficiency term u_{it}. The noise term is usually assumed to be random with zero mean, whereas the inefficiency term is strictly positive and assumed to follow a half-normal, truncated-normal or exponential distribution. :

$$u_{it} \sim N^{+}(z'_{it}\delta, \sigma_u^2) \tag{3.1}$$

$$E(\ln y_{it}) = \beta_0 + \sum_n \beta_n \ln x_{nit} + E(v_{it}) - E(u_{it}) \tag{3.2}$$

$$= \beta_0 + \sum_n \beta_n \ln x_{nit} - \left\{ z'_{it}\delta + \frac{\emptyset(\frac{z'_{it}\delta}{\sigma_u})}{\Phi(\frac{z'_{it}\delta}{\sigma_u})} \right\}$$

y_{it} and x_{nit} represent the output and the exogenous explanatory variables *n* for ANSP *i* in year *t*. The inefficiency term u_{it} is half normal distributed and positive with mean $z'_{it}\delta$. The noise term is v_{it} and $\emptyset(\cdot)$ and $\Phi(\cdot)$ are the density and cumulative distribution functions of the standard normal variable respectively. We apply the same model to estimate a Cobb-Douglas cost function, which represents a log-linear relationship between cost, input prices, output level and exogenous drivers. Since a cost frontier must be linearly homogeneous in inputs prices, the parameter restriction $\beta_k = 1 - \sum_{n \neq k} \beta_n$ must be imposed prior to estimation (Kumbhakar and Lovell, 2000).

$$ln(\frac{E_{it}}{w_{kit}}) = \beta_0 + \beta_y \ln y_{it} + \sum_{n \neq k} \beta_n \ln(\frac{w_{nit}}{w_{kit}}) + v_{it} + u_i \tag{3.3}$$

where costs E_{it} are logarithmically transformed. The explanatory variables, W_{nit}, are normalized and logarithmically transformed factor prices *n* per unit *i* per year *t* and the output level is y_{it}.

3.2 European ANSP dataset

The Performance Review Unit publishes an annual report, which presents a range of key performance indicators reflecting safety, quality of service and cost-effectiveness. We derive most of the data from the air traffic management cost-effectiveness benchmarking reports, which contain information on ANSP costs and revenues each year, reported separately for en-route and terminal control. They also report the output measures including instrumental flight rules (IFR) controlled, in kilometers and in hours, both en-route and with respect to movements around airports. Detailed input components include annual employment costs for air traffic controllers (ATCO) and support staff, the hours worked in air control centers, towers and approach centers and the net book value of fixed assets on the balance sheet. Airspace characteristics reported per ANSP include the maximum number of en-route sectors, traffic density, seasonality (equal to traffic levels in the peak month divided by average monthly traffic), size of airspace in square kilometers and traffic complexity. The complexity index represents an aggregate of structural complexity (derived from vertical, horizontal and speed interactions) and adjusted density. Indicators related to institutional settings include the form of ownership with a distinction between a state agency [AGENCY], a government-owned corporation [CORP], or a public-private joint venture, which is the default in all regression results. Additional economic indicators include the purchasing power parity index, intermediate goods and energy price index, exchange rates and inflation rates which have been collected from the OECD[3] and Eurostat[4] datasets.

Data quality is an important element of the statistical analysis. Many of the numbers were collected manually from annual reports which increases the probability of errors. In addition, there may be inconsistencies in the numbers reported for one ANSP over time. In a few instances, this is caused by a change in the construction of the indicator. We conducted checks on the evolution of all relevant indicators per ANSP and applied corrections where necessary based on the imputation technique, with linear interpolation of values for one

[3] https://data.oecd.org/conversion/purchasing-power-parities-ppp.htm
[4] http://ec.europa.eu/eurostat/web/purchasing-power-parities/data/database

variable based on the evolution over time for another variable[5]. We found errors in the reports and have corrected them accordingly. We note that from 2006 to 2008 and in 2010, the number of flight kilometers published in the reports is defined as 'distance' whereas other years utilize flight km. The 'distance' variable was incorrect for MUAC, Germany, Belgium and the Netherlands due to double counting. We note that the IFR airport movements reported for Greece in 2014 is three times higher than in 2013 which could be an error. Finally, new variables were added to the reports from 2010, including seasonality. We assume that the 2010 values remained consistent in the earlier years. In addition, we assume that the maximum number of sectors remains constant. We also dealt with missing data through imputation based on linear interpolation of values for the same variable in neighboring ANSPs (or countries)[6]. After performing these checks, we obtain a representative panel dataset of 37 ANSPs covering nine years (2006-2014), with no drastic jumps or structural breaks over the time frame. The panel is close to being balanced although ARMATS (Armenia) is missing for the years 2006 to 2008. The dataset is available from the authors for purposes of replicability.

From the dataset, we construct a number of indicators that are applied in the SFA as listed in Tables 1 and 2.

Table 1: Variables in stochastic frontier cost function

Dependent Variable	
	$\frac{\text{total cost}}{\text{cost of operation index}}$
Independent Inputs	
Output	total IFR flight hours controlled (en-route) and total IFR airport movements (terminal)
Labor	$\frac{\text{total staff cost/ATCO hours}}{\text{cost of operation index}}$
Capital	$\frac{(\text{depreciation cost} + \text{cost of capital}) / (NBV / \text{capital goods price index})}{\text{cost of operation index}}$
Environmental Variables	

[5] For example, evolution of "staff cost in en-route control" for Finavia is imputed using interpolation based on the evolution of "total cost in en-route control" for Finavia.
[6] For example, we impute missing values on "cost of capital" for Croatia, based on observations in Serbia and in Slovenia.

Airspace characteristics	seasonality, complexity
Ownership form	state agency, government corporation, public-private firm

where the cost of operation index = intermediate goods and energy price index $* PPP$, $PPP = \frac{\text{Purchasing power parity}}{\text{Exchange rate}}$ and NBV = net book value.

In order to ensure comparability, monetary indicators are standardized using purchasing power parity and a cost of operation index. Standardization ensures that the econometric cost function is homogeneous and in alignment with the underlying economic theory on production and cost functions (Coelli et al., 2005).

Table 2: Variables in stochastic frontier production function

Dependent Variable		
	En-route	*Terminal*
	total IFR flight hours controlled	total IFR airport movements
Independent Inputs		
Labor	ATCO hours in air control centers	ATCO hours in approach centers and towers
Capital	maximum number of en-route sectors	$\frac{NBV}{\text{capital goods price index}} * \text{ppp}$
Environmental Variables		
Airspace characteristics	seasonality, complexity	
Ownership form	state agency, government corporation, public-private firm	

We note that the capital indicator in the terminal production function is based on the maximum number of en-route sectors rather than net book value because the former proved more statistically significant however, the latter still provides similar if less statistically significant results. Finally, we apply a logarithmic transformation to all continuous variables because of the log-linear characteristic of the Cobb-Douglas models.

3.3 Estimation of stochastic frontier cost and production functions

In this section, we first discuss en-route air traffic control and subsequently the terminal control market. We implement the estimations in STATA, using the tailor-made SFPANEL package (Belotti et al., 2012). We tested a number of alternative specifications including SFA with time decay in the inefficiency term (Battese and Coelli, 1992) and SFA with exogenous drivers affecting the distribution of the inefficiency term (Battese and Coelli, 1995). We only present the results of Battese and Coelli (1995) specification because this model provided the most promising estimations according to the log likelihood estimates.

In order to estimate the en-route air traffic control production function, we solve equations 3.4 and 3.5 simultaneously.

$$\ln(IFR\ flight\ hours_{it}) = \beta_0 + \beta_1 \ln(ATCO_{it}) + \beta_2 ln(sectors_{it}) + \beta_{Z1} \ln(seasonality_{it}) + \beta_{Z2} \ln(complexity_{it}) + v_{it} - u_{it} \tag{3.4}$$

$$U_{it} = \delta_1 \ln(complexity)_{it} + \delta_2 ownership[corp]_{it} + \delta_3 ownership[agency]_{it} + \tau_{it} \tag{3.5}$$

τ_{it} is a random variable defined by the truncation of the normal distribution (with a mean of zero and constant variance). u_{it} is expressed without an intercept which means that there is no constant element of inefficiency that is identical for all units at all times given the level of heterogeneity.

In order to estimate the en-route air traffic control cost function we solve equations 3.6 and 3.7 simultaneously.

$$\begin{aligned} ln\left(\frac{Total\ cost_{it}}{cost\ of\ operation\ index_{it}}\right) &= \beta_0 + \beta_1\, ln\left(IFR\ flight\ hours_{it}\right) + \beta_2 \ln\left(\frac{Labor\ cost_{it}}{cost\ of\ operation\ index_{it}}\right) \\ &+ \beta_3 \ln\left(\frac{Capital\ cost_{it}}{cost\ of\ operation\ index_{it}}\right) + \beta_{Z1} \ln(seasonality_{it}) \\ &+ \beta_{Z2} \ln(complexity_{it}) + v_{it} + u_{it} \end{aligned} \tag{3.6}$$

$$U_{it} = \delta_1 \ln(complexity)_{it} + \delta_2 ownership[corp]_{it} + \delta_3 ownership[agency]_{it} + \tau_{it} \tag{3.7}$$

The results of regression equations (3.4) to (3.7) are presented in Table 3 for the en-route air traffic control sector and in Table 4 for terminal control sector with the relevant, respective variables.

Table 3: En-route cost and production functions estimates

Enroute, cost

Para.	Label	Model 1 Estimate	Model 1 SE	Model 2 Estimate	Model 2 SE
Elasticities					
β_1	x_1 (Total IFR flight hours controlled)	0.919 **	0.016	0.905 **	0.018
β_2	x_2 (Labor cost)	0.385 **	0.035	0.417 **	0.041
β_3	x_3 (Capital cost)	0.216 **	0.021	0.218 **	0.022
Environmental variables					
β_{Z1}	Z_1 (Seasonality)	1.379 **	0.192	1.686 **	0.214
β_{Z2}	Z_2 (Complexity)			0.700 **	0.153
Exogenous inefficiency determinantsa					
δ_1	Z_{u1} (Complexity)			-0.846 **	0.133
δ_2	Z_{u2} (Ownership gov/corp)			1.596 **	0.337
δ_3	Z_{u3} (Ownership agency)			1.563 **	0.344
	sigma_u	**0.080**	**2.463**	**0.296** **	**0.025**
	sigma_v	**0.327** **	**0.013**	**0.181** **	**0.022**
	lambda	**0.246**	**2.466**	**1.633** **	**0.041**
	Log Likelihood	**-97.510**		**-57.280**	

Enroute, production

Para.	Label	Model 1 Estimate	Model 1 SE	Model 2 Estimate	Model 2 SE
β_1	x_1 (Labor)	0.451 **	0.074	0.423 **	0.060
β_2	x_2 (Capital)	0.582 **	0.084	0.520 **	0.064
β_{Z1}	Z_1 (Seasonality)	-1.017 **	0.232	-2.492 **	0.200
β_{Z2}	Z_2 (Complexity)			-0.989 **	0.102
δ_1	Z_{u1} (Complexity)			-1.553 **	0.102
δ_2	Z_{u2} (Ownership gov/corp)			2.935 **	0.225
δ_3	Z_{u3} (Ownership agency)			2.623 **	0.232
	sigma_u	**3.723**	**25.244**	**0.340** **	**0.023**
	sigma_v	**0.271** **	**0.029**	**0.142** **	**0.019**
	lambda	**13.745**	**25.237**	**2.395** **	**0.037**
	Log Likelihood	**-150.271**		**-59.249**	

A */** next to coefficient indicates significance at the 5%/1% level.

[a] A positive efficiency score parameter estimate shows that the variable has a negative effect on efficiency

In Table 3 we present the results of the stochastic production and cost functions for en-route operations and in Table 4 we present the equivalent for terminal operations. Each of the SFA production and cost estimates in Tables 3 and 4 include two models. The first model does not limit the average distribution of the inefficiency. When such a model was not able to explain the inefficiency (σ_u was not significant), we then included explanatory variables to describe the mean of the distribution of the inefficiency. The σ_u and λ in Models 1 are usually insignificant hence the complexity and ownership variables are clearly an important element in explaining ANSP inefficiency levels (except for the analysis of the terminal production function in which σ_u of model 1 is significant).

All variables in the Cobb-Douglas functions proved highly significant across all models. In the cost analysis, with respect to output, it is clear that there are small economies of scale ranging from 10 to 13%. Furthermore, labor is significantly more important than capital, which is represented as their proportions in the total cost functions. The environmental variables are highly significant and with the expected signs. Seasonality and complexity both increase costs. However, complexity both increases costs and reduces inefficiency. We assume that additional complexity would appear to require a consistent and professional management that is better able to utilize labor resources. Hence, the higher the complexity index, the more efficient the ANSP would appear to be. As noted by Nero and Portet (2007), higher traffic density allows for more effective use of existing resources and the potential to exploit scale effects which are likely to be significant given the fixed infrastructure costs. Consequently, it would appear that beyond the economies of scale estimated by the output variables in the cost function, additional economies are likely available. Furthermore, it would appear that the public private partnership model creates substantial incentives, since the government ownership form variables decrease efficiency levels. This seems to suggest that under government ownership, a relatively large weight is placed on national interest, such as local suppliers and labor unions. This is confirmed by analysis focusing specifically on the role and preferences of unions (Blondiau et al., 2017). The state agency variable, which represents ANSPs that belong to the Department of Transport or Civil Aviation Authority, are the most directly connected to the government and show similar levels of inefficiency to those of a government corporation. In line with Section 2, it would appear that greater emphasis is placed on national interests rather than consumer surplus.

Based on the results of Models 2 of the en-route analyses presented in Table 3, Figures 1a and 1b present average production and cost efficiencies for the 37 countries over the nine years of analysis, and Figures 2a and 2b present the average production and cost efficiencies per ANSP.

Figure 1a: Average production efficiency for en-route ANSPs from 2006 to 2014

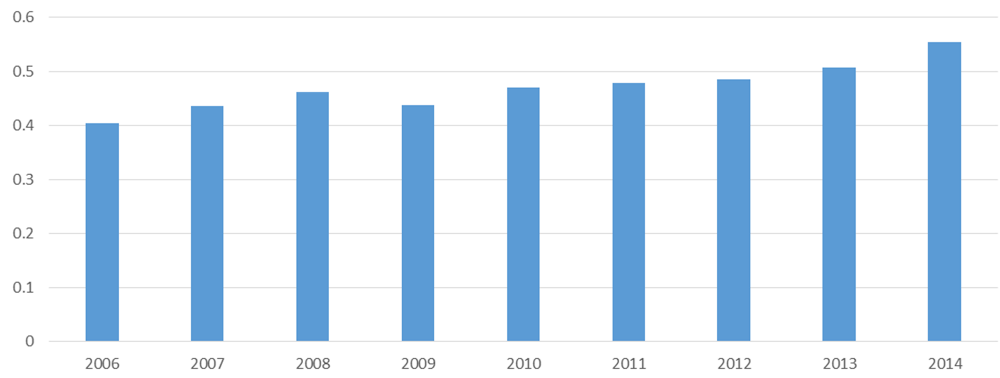


Figure 1b: Average cost efficiency estimates for en-route ANSPs from 2006-2014

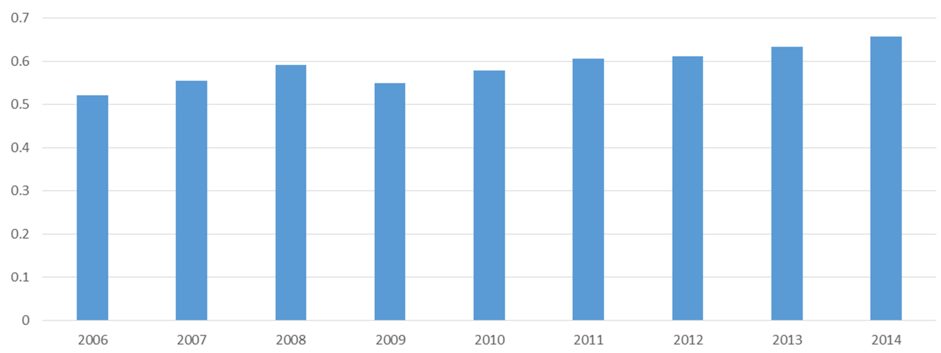


Figure 1a shows that the average production efficiency estimates gradually improve from 0.40 to 0.55 with a dip in 2009 due to the financial crisis, which reduced air traffic movements substantially. Efficiency scores in the cost analysis of Figure 1b are slightly higher, ranging from 0.52 to 0.65. Figures 1a and 1b therefore indicate that efficiency trends over time are positive although the levels of inefficiency on average remain substantial by 2014. This means that the average ANSP is 45% less productively efficient than the best performing ANSP and 35% less cost efficient than the best performing ANSP. On the other hand, the averages mask large, statistically different estimates across the ANSPs, as presented in Figure 2a and 2b. When comparing average efficiency levels across ANSPs, we see that the efficiency levels of ten of the ANSPs lie above 0.7 with MUAC, NATS and SkyGuide at the top. Eighteen of the smallest ANSPs scores lead the bottom of the rank with efficiency estimates below 0.4. As noted above, the cost efficiency scores are slightly higher so that only seven countries lie below 0.4. In Appendix A.1 and A.2, we present the complete set of efficiency levels per ANSP over time for en-route production and cost efficiency estimates. Of the more inefficient ANSPs, we do note that some show consistent improvements such as Albcontrol, BULATSA, DCAC Cyprus, EANS, MATS, MoldATSA and Romatsa.

Figure 2a: Average production efficiency estimates per en-route ANSP

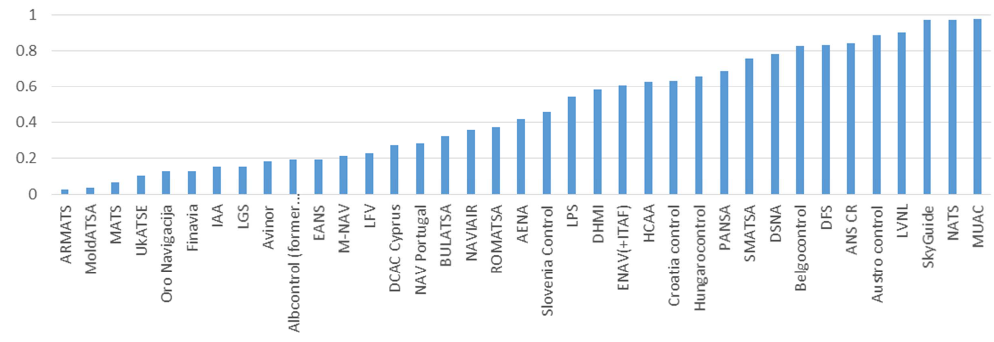
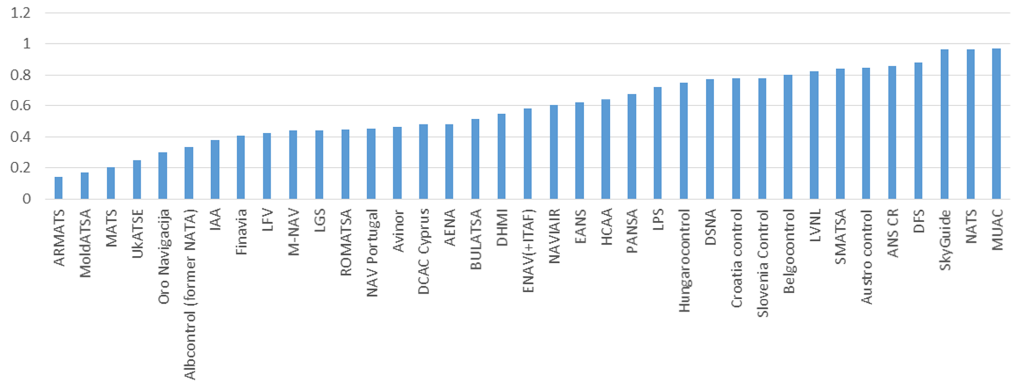


Figure 2b: Average cost efficiency estimates per en-route ANSP



In Table 4, we present the SFA cost and production estimates for the terminal control activities of the ANSPs. We note that terminal activities are reported at the country level hence aggregate air traffic control procedures at large hub airports and small, regional spokes may lead to less reliable comparisons. Furthermore, the outsourcing of terminal activities at some of the airports in the UK, Germany and Sweden may also lead to changes over time although it is still too early to analyze statistically. As with the en-route cost function, all variables in the terminal cost function are statistically significant with signs as would be expected. The second model proved the most relevant with both complexity and ownership form explaining the levels of inefficiency. Again, small economies of scale are estimated of around 13%. Increased complexity appears to improve efficiency levels, which may indicate supplementary economies of scale caused by the additional workload required to handle the complexity. Ownership form also impacts terminal ANSP activities with the state agency approach causing slightly higher levels of cost inefficiency compared to the government corporation which in turn adds substantial cost inefficiency above and beyond the public-private form. However, terminal production would not appear to be impacted by the ownership form and model 1 is sufficient to describe the function. However, the second model better explains the production function, as proven by the decrease in the log likelihood value and the likelihood-ratio test (shown below in Table 5), probably due to the inclusion of complexity in the production function.

Table 4: Terminal control cost and production functions estimates

Terminal, cost

Para.	Label	Model 1 Estimate		Model 1 SE	Model 2 Estimate		Model 2 SE
Elasticities							
β_1	x_1 (IFR airport movements)	0.841	**	0.020	0.874	**	0.019
β_2	x_2 (Labor cost)	0.454	**	0.037	0.492	**	0.043
β_3	x_3 (Capital cost)	0.072	**	0.022	0.053	**	0.013
Environmental variables							
β_{Z1}	Z_1 (Seasonality)	2.337	**	0.210	2.310	**	0.229
β_{Z2}	Z_2 (Complexity)				0.194	*	0.080
Exogenous inefficiency determinantsa							
δ_1	Z_{u1} (Complexity)				-0.548	**	0.077
δ_2	Z_{u2} (Ownership gov/corp)				1.280	**	0.164
δ_3	Z_{u3} (Ownership agency)				1.372	**	0.171
	sigma_u	**1.180**		**1.521**	**0.418**	**	**0.026**
	sigma_v	**0.246**	**	**0.035**	**0.082**	**	**0.024**
	lambda	**4.401**	**	**1.498**	**5.068**	**	**0.037**
	Log Likelihood			**-135.581**			**-101.612**

Terminal, production

Para.	Label	Model 1 Estimate		Model 1 SE	Model 2 Estimate		Model 2 SE
β_1	x_1 (Labor)	0.537	**	0.029	0.594	**	0.031
β_2	x_2 (Capital)	0.472	**	0.020	0.399	**	0.270
β_{Z1}	Z_1 (Seasonality)	-2.884	**	0.155	-3.147	**	0.037
β_{Z2}	Z_2 (Complexity)				0.072	*	0.172
δ_1	Z_{u1} (Complexity)				-0.640		0.935
δ_2	Z_{u2} (Ownership gov/corp)				-0.369		1.025
δ_3	Z_{u3} (Ownership agency)				-0.441		1.222
	sigma_u	**1.022**	**	**0.235**	**0.565**	*	**0.282**
	sigma_v	**0.184**	**	**0.012**	**0.230**	**	**0.017**
	lambda	**5.543**	**	**0.236**	**2.453**	**	**0.279**
	Log Likelihood	**-71.139**			**-52.122**		

A */** next to coefficient indicates significance at the 5%/1% level.

[a] A positive efficiency score parameter estimate shows that the variable has a negative effect on efficiency

In Figures 3a and 3b we present changes in terminal efficiencies over time and in Figures 4a and 4b we detail the average terminal efficiency scores per ANSP in ascending order. Tower control providers also suffered substantially in 2009 as a result of the financial crisis and subsequent reduction in air traffic movements. The largest impacts are clearly shown with respect to the production function which highlights the fact that the ANSPs only recovered on average in 2014. Average cost efficiency levels were also impacted in 2009 but gradually improved over time reaching their highest levels by 2014. However, we also note that average cost efficiency estimates peak at around 0.59 by 2014 hence although the trend is positive, the low levels of efficiency are rather substantial.

Figure 3a: Average terminal production efficiency estimates from 2006 to 2014

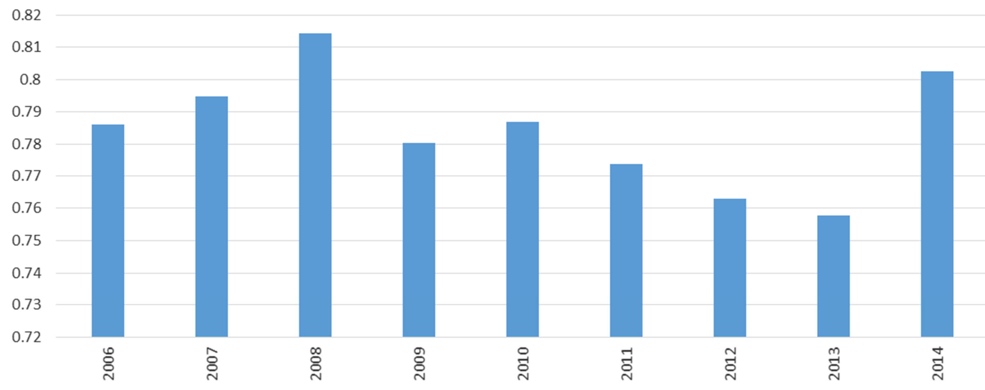
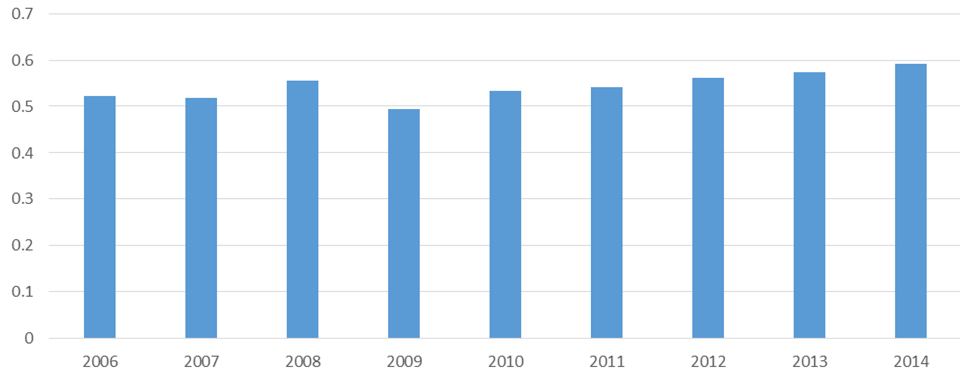


Figure 3b: Average terminal cost efficiency estimates from 2006 to 2014



Whilst the average production and cost efficiency estimates lie around 0.8 and 0.6 in 2014 respectively, this masks large heterogeneity across the providers as presented in Figures 4a and 4b. Cost efficiency estimates range from 0.12 for the Armenian ANSP to 0.92 in Switzerland and Germany. The efficiency estimates show a mix across the continent with Slovenia and Croatia performing relatively better than some of the Western European countries, including Sweden and France. We tested the difference between the mean inefficiency scores in the Eastern and Western European countries in each of the four models. The results of the tests suggest that there is a statistically significant difference (99%) between the averages in each of the models.

Figure 4a: Average terminal production efficiency estimates

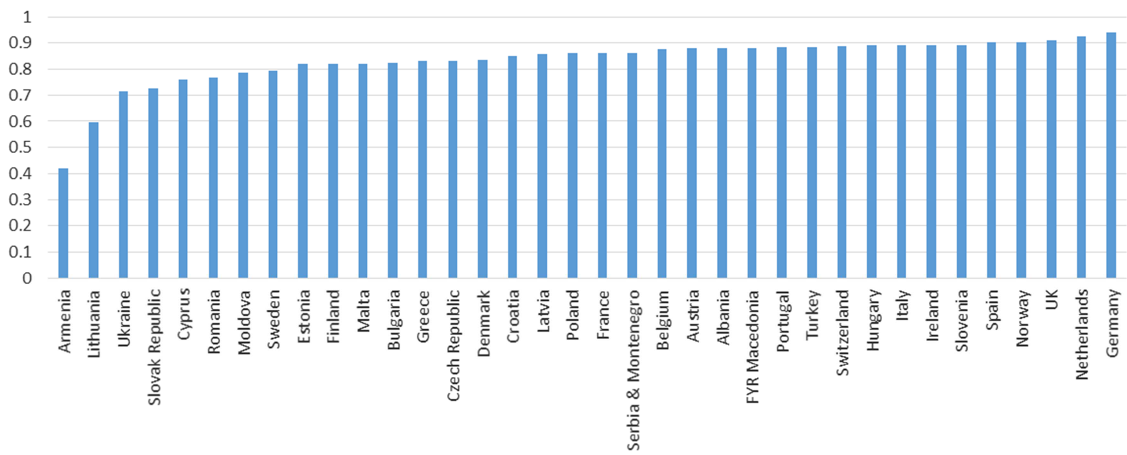
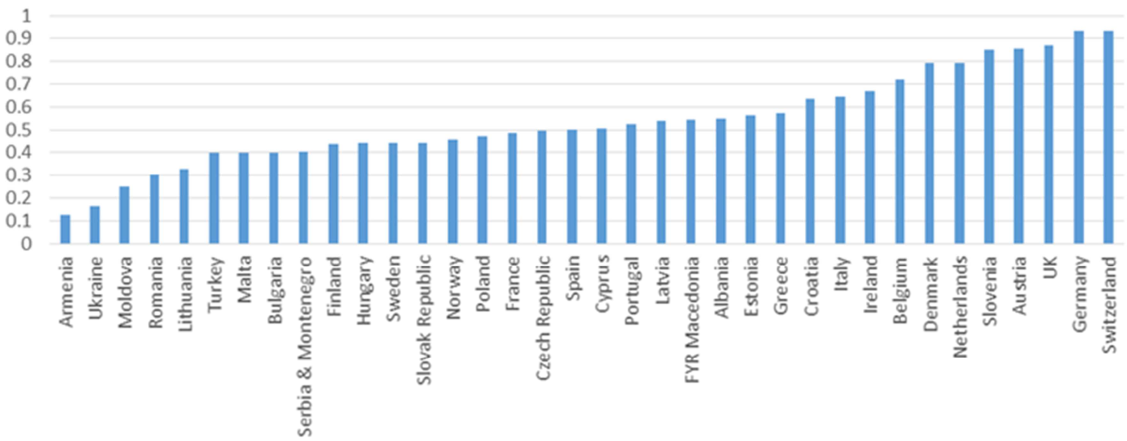


Figure 4b: Average terminal cost efficiency estimates



In Table 5, we present the results of likelihood-ratio tests which show that the second models better explain the production function and the cost function than the first, in addition to the high values of $\lambda>1$, which indicate that the inefficiency effects are highly significant. These tests were applied in order to compare the goodness of fit of the two models, one of which (the null model) is a special case of the alternative model. The likelihood-ratio (LR) test statistic, $LR = -2\{\log[Likelihood(H_0)] - \log[Likelihood(H_1)]\}$, has an approximate chi-square distribution with a parameter equal to the number of parameters assumed to be zero in the null hypothesis, H_o, provided H_o is true. The null hypothesis specifies that the complexity and the ownership variables are not taken into account when explaining the inefficiency effects of the production and cost functions[7]. This null hypothesis is rejected at the 1% level of significance.

[7] The degree of freedom equals the number of restrictions in the test which is 4.

Table 5: Tests of hypotheses for parameters of the ANSP inefficiency models

Null Hypothesis	Log(Likelihood)				$\chi^2(0.99)$	Test statistic*			
	production		cost			production		cost	
	terminal	en-route	terminal	en-route		terminal	en-route	terminal	en-route
H_0: $\delta_1 = \delta_2 = \delta_3 = 0$ $\beta_{Z2} = 0$	-71.14	-150.27	-135.58	-97.51	13.28	38.03*	182.04*	67.94*	80.46*
H_1	-52.12	-59.25	-101.61	-57.28					

* An asterisk on the value of the test statistic indicates that it exceeds the 99th percentile for the corresponding χ^2-distribution and so the null hypothesis is rejected.

The inefficiency effects in the stochastic frontier are related to both complexity and ownership form of the ANSPs, except for the terminal production model. Thus it appears that the inefficiency rankings drawn from the stochastic frontier production and cost functions (models 2) are a significant improvement over the corresponding stochastic frontier which does not include the exogenous variables (models 1).

In order to compare the efficiency rankings produced according to the stochastic production and cost functions, we present the Spearman's rank correlation coefficients in Table 6. The highest correlation of 0.95 is between en-route production and cost efficiency ranks. In other words, ANSPs that are productively efficient have also ensured cost or allocative efficiency in general. The terminal cost efficiency rankings are also reasonably in line with the en-route analyses.

Table 6: Spearman's correlation coefficients of efficiency rankings

	En-route - production		En-route - cost		Terminal - production	
En-route - cost	0.95	*				
Terminal - production	0.53	*	0.51	*		
Terminal - cost	0.58	*	0.64	*	0.64	*

A * next to coefficient indicates significance at the 1% level.

Consequently, we learn from these comparisons that certain countries utilize their resources relatively productively but fail to reach the same relative cost efficiency. We present the rankings for all ANSPs for all four models in Table 7. An examination of the data indicates that there are several countries that perform better in their en-route operations than their terminal operations, such as ANS CR in the Czech Republic, LPS in the Slovak Republic and SMATSA in Serbia & Montenegro. When comparing en-route cost efficiency rankings compared to the equivalent terminal ranking, we note that some countries are substantially less terminal cost efficient, such as the ANS CR in the Czech Republic, LPS in Slovak Republic and PANSA in Poland.

Table 7: Efficiency rankings according to all four SFA models

Country	ANSP	En-route - cost	En-route - production	Terminal - cost	Terminal - production
Spain	AENA	22	19	19	5
Albania	Albcontrol (former NATA)	32	28	14	14
Czech Republic	ANS CR	5	6	20	23
Armenia	ARMATS	37	37	36	36
Austria	Austro control	6	5	4	15
Norway	Avinor	24	29	23	4
Belgium	Belgocontrol	9	8	8	16
Bulgaria	BULATSA	21	22	29	25
Croatia	Croatia control	11	13	11	21
Cyprus	DCAC Cyprus	23	24	18	32
Germany	DFS	4	7	2	1
Turkey	DHMI	20	16	31	11
France	DSNA	12	9	21	18
Estonia	EANS	17	27	13	28
Italy	ENAV(+ITAF)	19	15	10	8
Finland	Finavia	30	32	27	27
Greece	HCAA	16	14	12	24
Hungary	Hungarocontrol	13	12	26	9
Ireland	IAA	31	31	9	7
Sweden	LFV	29	25	25	29
Latvia	LGS	27	30	16	20
Slovak Republic	LPS	14	17	24	33
Netherlands	LVNL	8	4	6	2
Malta	MATS	35	35	30	26
FYR Macedonia	M-NAV	28	26	15	13
Moldova	MoldATSA	36	36	34	30
International	MUAC	1	1		
UK	NATS	2	2	3	3
Portugal	NAV Portugal	25	23	17	12
Denmark	NAVIAIR	18	21	7	22
Lithuania	Oro Navigacija	33	33	32	35
Poland	PANSA	15	11	22	19
Romania	ROMATSA	26	20	33	31
Switzerland	SkyGuide	3	3	1	10
Slovenia	Slovenia Control	10	18	5	6
Serbia & Montenegro	SMATSA	7	10	28	17
Ukraine	UkATSE	34	34	35	34

4. Conclusions

In this research we focus on the effect of ownership form and airspace characteristics on ANSP performance in Europe. Based on an economic model, we learn that effort to achieve efficiency will likely be higher in the case of public companies with a board of stakeholders and in the case of a private company where stakeholders are also shareholders, as is the case with MUAC, NATS and Skyguide. The impact of strong national interest, on the other hand, encourages technology purchases from local suppliers or relatively powerful labor unions which are likely to decrease efficiency. Furthermore, without much weight on consumer surplus, the probability of expending effort to achieve efficiency goals is rather low.

In addition, we estimate econometrically the cost and production functions of 37 European ANSPs over a nine year time frame. The coefficient estimates are significant and have the expected signs. We note that input prices for labor costs (wages) seems to carry a greater importance in comparison to capital costs. This observation may be explained by the higher share of labor costs at the ANSP total cost level currently. With respect to the cost function and economies of scale, we find that a 10% increase in traffic, given the same airspace, corresponds to a cost decrease of around 10 to 15% on average. Structural differences in air traffic characteristics between ANSPs are important in explaining productivity and efficiency performance differences. Seasonality and traffic complexity seem to be particularly relevant. The results of the models also show that complexity explains inefficiency levels but perhaps in an unexpected direction. Given the significant and negative value of the parameter, this suggests that the managers of ANSPs handling higher levels of complexity are more efficient, which could be explained as follows:

(a) complexity acts as a proxy for the careful need to manage such an airspace leading to experienced and efficient management;
(b) European airspaces are relatively small hence do not enjoy economies of scale. Complexity creates additional work, which in turn provides the opportunity for greater efficiency.

We find a consistent, positive time trend in levels of efficiency suggesting that, on average, the Single European Skies initiative has been encouraging improvements in cost and productive efficiency over time although much work remains. The significance of the ownership variables in most of the results clearly shows that the choice is fundamental and impacts the level of efficiencies directly. We find that private-public partnerships with stakeholders on boards achieve significantly higher productivity and cost efficiency. This suggests that state agencies and government corporations attach a much higher weight to national interests than to the airspace users.

Future directions include expanding the dataset to cover the United States (at the level of the air route traffic control centers), Canada, Australia and New Zealand in order to further develop the analysis and better understand the impact of fine-grained differences in ownership form and potential for economies of scale.

Acknowledgment

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Appendix: Stochastic Frontier Analysis results per Air Navigation Service Provider

Figure A.1: En-route production efficiency estimates per ANSP from 2006-2014 (sorted alphabetically)

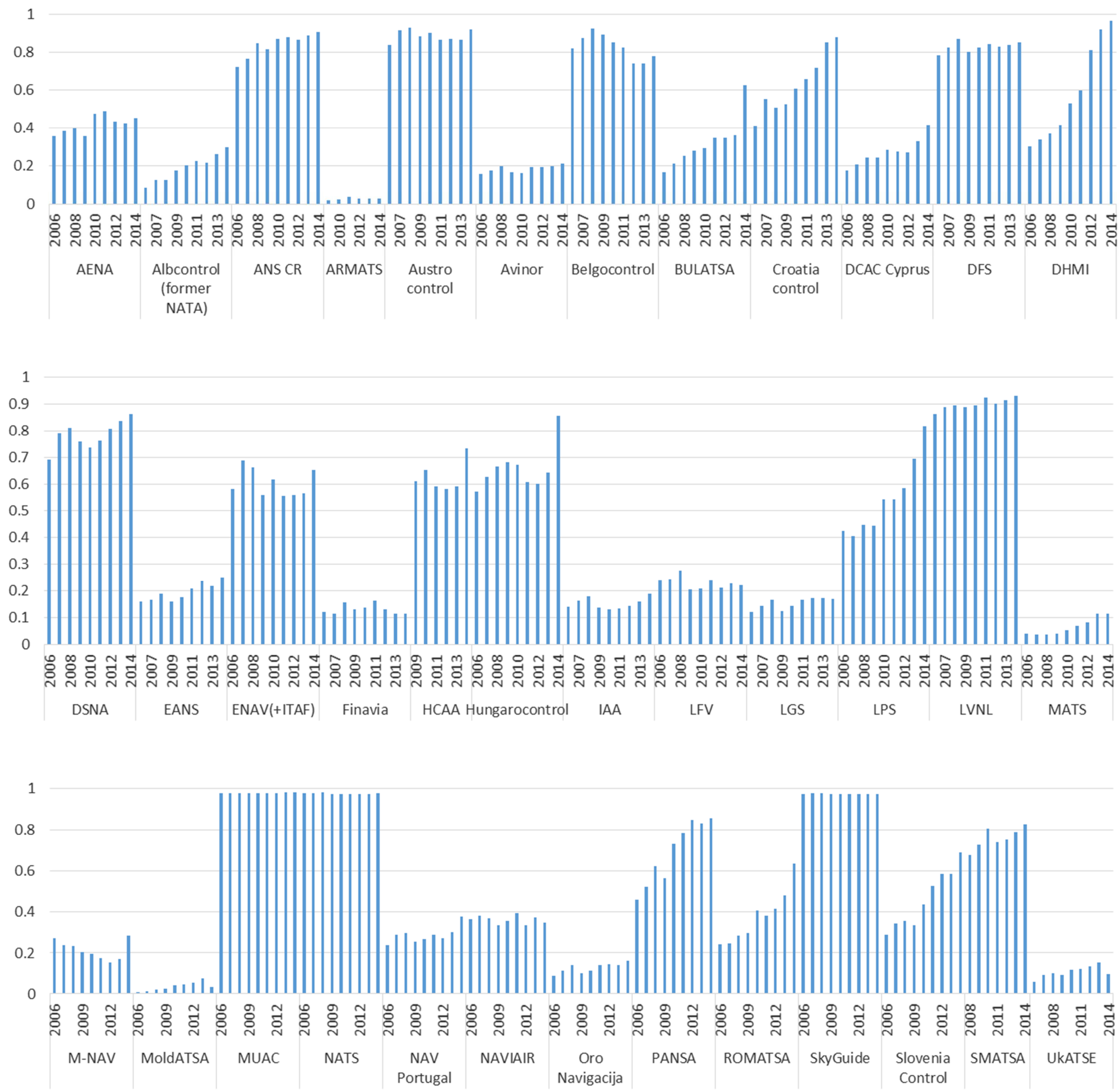

Figure A.2: En-route cost efficiency estimates per ANSP from 2006-2014 (sorted alphabetically)