Swiss International and Regional Airports - an Efficiency Benchmarking

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We benchmark the three international and two of the four main regional Swiss Airports against a representative set of 112 European airports based on a stochastic frontier analysis with an input-oriented, multi-output distance function that we estimate based on a Cobb-Douglas production function. For the regional airports, we apply depreciation as a capital proxy whereas, for the international airports, we provide one estimation with runway length and one with depreciation. Outputs are measured by air traffic movements, passenger and cargo volumes, and non-aeronautical revenues; in addition, our setting includes minority/majority privatization and slot constraints as institutional variables. For the international airports, we fail to estimate a significant production function with all three outputs simultaneously; however, in one model, we find that efficiency is higher with privatization and with slot constraints, which is in-line with the literature. For the regional airports, the non-aviation revenues and privatization are not available but the estimation returns significant coefficients for the production function and for slot constraints; nonetheless, the efficiency of regional airports that exploit non-aviation activities may be underestimated. These results illustrate that the efficiency measurement hinges on the availability of input and output data, the model specification, and the choice of a suitable capital proxy.

Keywords: Swiss Regional Airports; Swiss International Airports; Airport Benchmarking; Stochastic Frontier Analysis; Technical Efficiency.

JEL classification: C44, D24, H54, L51, L93.

Introduction

Airports are important parts of a country's infrastructure. They benefit the local economies directly by connecting remote regions and enabling the transmission of goods, services, and information, as well as indirectly, by generating investment opportunities and the agglomeration of economies (Button and Taylor, 2000). However, while efficiently functioning airports ensure connectivity, their capital-intensive operational requirements may be difficult to be sustained (Adler et al., 2013, p.23). Moreover, the room for capacity expansions at most airports operating near capacity are usually limited due to geographical, environmental, and political constraints. Therefore, input-output efficiency is key in airport operations.

Oftentimes, regional airports face low demand and missing scale economies, which makes their economic sustainability a challenge, so that many regional airports are publicly subsidized. The economic rationale for those subsidies consists in positive externalities arising from connectivity and other indirect and direct economic effects of airports. However, while connectivity and airport services may be underprovided without public funding, the subsidies may deter airports from improving the efficiency in their operations, so that they are not allocated efficiently. In this respect, certain costs such as, e.g., runway maintenance are independent from demand for airport services and airport management; by contrast, other

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costs depend on airport management, such as an efficient utilization of inputs or an optimal operational organization. As a result, there may be opportunities for efficiency improvements within the scope of the airport management that optimize the input resource allocation without decreasing operational output. Moreover, for airports without expansion opportunities, the development of the aviation infrastructure may focus on the optimization of the existing facilities, which is achieved by increasing the efficiency of processes and resource utilization (FOCA, 2016). In this case, where management oversees the efficiency and optimization of the existing infrastructure through its choice of a successful revenue strategy and its selection of inputs for efficient airport production (Adler and Liebert, 2014).

For the above reasons, a broad field of studies emerged that investigates airport efficiency. However, while many previous benchmarkings focus on comparisons between international airports in Europe, which may include the data of the international airports of Zurich, Geneva, and Basel, or on comparisons of national airports within various European countries, the Swiss regional airports' efficiency was not investigated yet. At the same time, many studies stress that the relevance of different efficiency drivers may depend on the national context. These arguments motivate an international case study that investigates the relative efficiency of both the international and regional airports in Switzerland.[3]

Thus, the study at hand provides a technical efficiency benchmarking of the three international and two of the four main regional Swiss airports against a representative set of 112 European airports based on a stochastic frontier analysis (SFA). We investigate the international airports Zurich, Geneva, and Basel-Mulhouse, as well as the regional airports Lugano-Agno and Bern-Belp. For the analysis, we choose an input-oriented, multi-output distance function that includes country and time effects, and controls for the institutional conditions of slot-coordination and airport ownership (i.e., the degree of privatization). The inputs are labor, capital, and other inputs, where capital is either approximated by physical runway lengths or financial depreciation. In this respect, the input orientation best suits the problems for airport managers who face exogenous airport demand and passenger traffic, thereby optimizing airport operations through an optimal allocation of their inputs.

For the international airports, the measured outputs are air traffic movements (ATM), passenger and cargo volumes, and non-aviation revenues. However, although we provide one estimation with runway length and one with depreciation as a capital proxy, we fail to estimate a significant production function with all three outputs simultaneously. Nonetheless, within the runway length model, we find that efficiency is higher with privatization and with slot constraints, which is in-line with the literature. For the regional airports, output is limited to air traffic movements and passenger and cargo volumes due to data availability. As a result, we find that depreciation represents a suitable capital proxy while physical runway length does not yield a valid model. In addition, the absence of non-aviation revenues and airport ownership information may underestimate the efficiency of airports that exploit non-aviation activities and airport privatization. These results illustrate that the efficiency measurement hinges on the availability and choice of input and output data, the model specification, and the choice of the capital proxy. Moreover, due to the parametric nature of the production function, the efficiency evaluation also relies on the functional form for airport technology and the orientation of the stochastic frontier.

[3] The study at hand is preceded by Kansikas (2017), which investigates the Swiss airport system in a descriptive manner.

Hence, the benchmarking at hand contributes to the literature by investigating the technical efficiency of the Swiss international and regional airports in a European context, and by illustrating the issues of applying different capital proxies and input prices. Nonetheless, when complemented with background information on sources of inefficiency, its results may be of interest to policymakers, airport managers, and researchers who are interested in benchmarking or ameliorating the economic sustainability and performance of international or regional airports. In addition, the data treatments applied illustrate how cross-country comparability is achieved in real terms, and how nominal input costs can be transferred into proxies for real input quantities.

Background

In Switzerland, there are three international airports, eleven regional airports, and many small regional airports and airfields. The national airports ensure connectivity in global service and supply chains whereas the larger regional airports cater to a smaller amount of scheduled passenger traffic and business jets. Finally, many small regional airports and airfields are used for medical flights, maintenance, and flight training activities (Wittmer and Bieger, 2011). According to the Swiss topography, these airports are mainly located in the Western and Northern parts of the country as well as South of the Alps. As domestic point-to-point transport mainly relies on land-based transport modes, air travel within the country is rather sparse. Regional airports mainly provide a few direct international flights, serve as hub gateways, for local holiday charters, and for the business and general aviation.

The three international airports of Switzerland are Zurich-Kloten (ZRH), Geneva-Cointrin (GVA), and Basel-Mulhouse (BSL).[4] Zurich airport serves as the main hub for Swiss International Airlines, the national carrier of Switzerland, while Geneva provides a gateway for Swiss and the Star Alliance to the western part of the country and near France. Both Basel and Geneva also provide hubs for the low-cost carrier Easy Jet, which holds a market share of 57% and 40% at the two airports (EasyJet, 2017), and serve as cargo hubs. By contrast, the eleven regional airports are dispersed across the nation. Only four of them provide scheduled or regular charter air services: Bern-Belp (BRN), Lugano-Agno (LUG), St. Gallen-Altenrhein (STG), and Sion (SIO). Bern and Lugano represent hub gateways to Munich and Zurich, respectively, and serve for business and the general Aviation; in addition, Bern hosts the federal government's flight services. St. Gallen is a private airport that offers scheduled flight services to Vienna and seasonal holiday charter flights for eastern Switzerland and the North-Western region of Austria. Sion is a mixed military and civil aviation airport, providing charter flights, a competence center for business aviation maintenance, repair and overhaul (MRO) as well as sparsely scheduled local air traffic. The remaining seven small regional airports, which are located mostly in the north-western part of Switzerland, serve for recreational and private use.[5]

[4] Basel is a joint public airport owned by Switzerland and France.

[5] Data availability for this study restricts the analysis to the three international airports and to Bern and Lugano.

Table 1: Swiss International & Regional Airports - Characteristics

Airport	Ownership	Passengers (Tsd.)	% of Switzerl.	ATM	% of Switzerl.
			International Airports		
ZRH	private	26’281	52.6%	265’100	18.4%
GVA	public	15’771	31.5%	188’829	13.1%
BSL	public	7’061	14.1%	94’359	6.6%
Subtotal			**98.2%**		**38.1%**
			Regional Airports		
BRN	private	189.2	0.4%	50’794	3.5%
LUG	public	167.0	0.3%	21’262	1.5%
STG	private	101.3	0.2%	27’301	1.9%
SIO	public	32.6	0.1%	41’016	2.8%
Subtotal			**1.0%**		**9.8%**
Total			**99.2%**		**47.9%**

Data: 2015

As Table 1 shows, the international as well as the small regional airports feature both private and public ownership forms while independent organization units manage all airports. However, as the cases of Geneva, Basel, Lugano and Sion indicate, public ownership is still prevalent. Moreover, Table 1 indicates the relative importance of the seven main airports that host scheduled air traffic are provided: international airports account for nearly all passenger traffic, with Zurich airport accounting for the main share. By contrast, air traffic movements (ATM), which include commercial and non-commercial movements and thus include also non-passenger traffic, are distributed more evenly. The seven main airports cover about half of the traffic volume. The importance of the international airports increases when only commercial ATM’s are evaluated, as most regional airports mainly cater private air traffic (cf., e.g., FOCA, 2017).

Previous Studies

As Adler et al. (2013, p.23) delineate, three prominent methodologies exist for the assessment of efficiency: data envelopment analysis (DEA), total factor productivity (TFP), and stochastic frontier analysis (SFA). DEA models explain inefficiencies in relation to a data envelope, which is based on minimal extrapolation (Bogetoft, 2012, p.71); TFP constructs an index to compare the outputs achieved with a specific set of inputs to capture airport specific production in economic terms. **By contrast,** SFA models relate observed outputs to a production function that extends the deterministic physical input specification by adding stochastic noise and inefficiency (cf. Martin et al., 2009, p.165).

Thus, DEA and TFP represent approaches to benchmarking in a non-parametric framework that do not require any specific functional form assumptions whereas the SFA approach relies on a parametric production function, which requires structural assumptions about the distribution of the parameters to be estimated, on the structure of the production possibility set, and the data generation process. **As a result**, DEA and TFP abstract from structural presuppositions but are deterministic, while SFA requires parametric assumptions but allows us to separate deterministic inefficiency from stochastic error terms, given the assumed structure is realistic (Bogetoft 2012, pp.111). **Consequently**, SFA is applied to disentangle factors related to airport management from environmental and fixed factors outside of the scope of airport managers. Compared to the other efficiency evaluation techniques, this method allows us to distinguish between exogenous and endogenous efficiency constraints, **thereby** providing a ranking of airport performance based on improvements that could be achieved through improvements of the use of inputs. Overall, most airport benchmarking studies apply either the SFA or the DEA approach while the estimation of TFP rarely occurs due to its high requirements on input and output price information (Adler et al., 2013, p.23).

The recent literature produced a solid body of empirical airport efficiency benchmarking studies based on SFA and DEA, both in national and international contexts. For example, Adler et al. (2013) benchmark a balanced panel of 85 EU Airports from 2002-2009 based on a DEA using the total number of passengers and cargo volume, the air traffic movements, and the non-aeronautical revenues as outputs and labor costs, other input costs, and runway length as inputs. Apart from applying financial depreciation, we draw on their input and output choice in the study at hand. By applying variable returns to scale and by separating discretionary from non-discretionary inputs, their analysis identifies inefficiencies ranging from 25 to 50 percent compared to the optimum, based on excess cost increases over time. In addition, their second-stage regression reveals that own ground-handling and fueling services increase airport inefficiency along with weak commercial activities and belonging to an airport group.

Similarly, Bubalo (2012) investigates a 2002 to 2010 panel of 139 European airports from 10 countries, where he relates depreciation, originating and inbound transfer passengers and costs as input variables to the airports' EBITs, revenues, and departing and terminating passengers; his main contribution is methodological, as he defines a new profitability-based specification which eliminates the need to classify airports based on other characteristics related to their size. Oum, Yan, and Yua (2008) provide one of the first studies evaluating the effect of ownership on a set of worldwide airports. In similar fashion Adler and Liebert (2014) investigate the efficiency of 43 airports from 13 European countries in a time range from 1998 to 2007, thereby finding that ownership form yields different effects as a function of an airport's competitive environment: if competition is low, private airports operate more efficiently than public airports. In all competitive settings, mixed private-public airports are less cost efficient than all other airports. Martin et al. (2009) investigate the Spanish airport system and find important inefficiencies and economies of scale in airport operations. Scotti et al. (2010) evaluate the impact of competition on the technical efficiency of Italian airports. They find that the intensity of competition yields a negative impact on the airport's exploitation of available inputs because passengers are easily diverted to nearby airports of substitution, and that publicly owned airports are more efficient than privately owned airports in their country. For a comprehensive survey of airport benchmarking studies, see Tovar and Martín-Cejas (2010), Liebert and Niemeier (2013), and Iyer and Jain (2019).

We prefer the SFA approach for our analysis due to its error decomposition, where the stochastic error term captures random deviations from optimal production while an inefficiency term denotes the inefficiency of the production unit concerned (e.g., Bogetoft, 2012, p.117). However, although we apply generic prices to construct internationally comparable real costs and input quantity proxies, we do not dispose of accurate market prices for the productive inputs. Therefore, we concentrate on the evaluation of technical efficiency, which denotes the relation of input quantities to the production outputs but abstracts from cost considerations and, hence, from productive, allocative, and cost efficiency (cf. Bogetoft, 2012, p.34).

As noted, the SFA framework requires the choice of a parametric production function that represents the technology used by all observation units in the set (Kumbhakar, Wang, and Horncastle 2015, p.13). The two most popular production functions are the Cobb-Douglas (CD) and the Translog (TL) form: While the former is known for its simple structure and its ability to track efficiency changes well, its functional form is nested in the Translog form and, therefore, is rather restrictive (Bogetoft 2012, pp.108). By contrast, the latter provides more flexibility to fit the data but may yield insensible results in an economic sense (Davis and Garcés 2009, p.134). For its above characteristics, we chose the Cobb-Douglas function.

Parmeter and Kumbhakar (2014, p.51) suggest complementing the estimation with an overview of the exogenous sources of inefficiency in the setting of interest to distinguish those inefficiency-inducing factors that can be influenced by airport management from those constraints that are exogenous. Exogenous factors may be based on the institutional structure in which the airport operates, whereas other exogenous constraints may be environmental, geographical, or political. In this respect, the literature highlights two key institutional variables that influence efficiency: the ownership structure of airports and the degree of competition. For instance, Oum, Yan, and Yua (2008) find that airports which are fully privately or fully publicly owned are more efficient compared to mixed-ownership airports. Similarly, Adler and Liebert (2014) argue that a uniform ownership structure might provide better incentives for airport management to achieve efficiency. However, these factors do not seem to yield univocal independent effects but, rather, may be country dependent.

Lastly, technical efficiency can be viewed from an input or output oriented perspective. While the former denotes the problem of minimizing inputs for a given output, the latter delineates maximizing output with a given number of inputs. Thus, when firms have more control over inputs than outputs, an input-oriented perspective is suitable (Coelli et al. 2005, p.264). In an airport setting, a large part of airport infrastructure are fixed-size capital goods that cannot be altered in the short run. Moreover, output in terms of air traffic movements, passenger and cargo volume is generally exogenous to the airport, as it is mainly determined by demand for flight services, so that input minimization seems to be the main managerial problem. For these reasons, the input-oriented perspective is appropriate to assess the efficiency of an airport in making use of its resources (Oum, Yan, and Yua 2008).

Model

As usual in the literature, we start with a deterministic Cobb-Douglas production function that specifies a single output y_{nt} of airport $n \in \{1, \dots, N\}$ at time t in log-linear form as a function

$$\ln y_{nt} = \beta_0 + \sum_i \beta_i \ln x_{nit} + \sum_k \delta_k \ln z_{nkt}$$

of $i \in \{1, \dots, I\}$ distinct productive inputs x_{nit}, a variety of $k \in \{1, \dots, K\}$ institutional variables z_{nkt}, β_i, δ_k as the respective coefficients, and intercept β_0. From the various inefficiency specifications, we choose Battese and Coelli (1992), which suggests that the single output y_{nt} of firm n at time t is determined by

$$y_{nt} = f(x_{nt}, z_{nt}; \beta) e^{v_{nt} - u_{nt}}$$

where $v_{nt} \sim N(0, \sigma_v^2)$ delineates a random error term with normal distribution and $f(x_{nt}, z_{nt}; \beta)$ represents the generic form of the production function based on input vector

x_{nt}, institutional variables z_{nt}, and coefficients β. Consequently, $u_{nt} \sim N^{+}(\mu, \sigma)$ represents the inefficiency of firm n at time t based on the truncated normal distribution N^{+}. Thus, inefficiency u_{nt} describes non-random output deviations from optimal production given the inputs x_{nt}, z_{nt} whereas error term v captures positive and negative random noise. Based on its distributional assumptions, this specification is referred to as the *normal-half normal* model (e.g., see Kumbhakar and Lovell 2000). Finally, due to $e^{-u} \leq 1$ by definition, technical efficiency TE is defined as

$$TE_{nt} = e^{-u_{nt}},$$

which is used to express the *relative output loss due to inefficiency* (E.g., Bogetoft and Otto 2011, 199 and p.218).[6] Battese and Coelli (1992) decompose the time-variant inefficiency into

$$u_{nt} = \exp[\eta(t - T)] \cdot u_n,$$

where $\exp[\eta(t - T)] \geq 0$ and $u_{nT} = u_n$, so that parameter η captures the impact of cross-sectional technological change which increases ($\eta > 0$) or decreases ($\eta < 0$) over time. As a result, the output variations due to technological changes enter the density function of u_{nt} rather than the deterministic part of the frontier, which allows us to separate technological change from the time-variance of inefficiency (cf. Coelli et al. 2005, 278).[7] Finally, inefficiency is estimated by parameter

$$\gamma = \frac{\sigma_u^2}{\sigma^2} \in [0,1],$$

which delineates the variance caused by inefficiency as a share of total variance.

The input-oriented view is adopted by converting the production function into an input oriented distance function, which, at the same time, solves the problem that a production function only accommodates a single output.[8] For this purpose, single output production function is expanded by introducing $j \in \{1, \ldots, J\}$ distinct productive outputs y_{njt} for each airport n at time t and its inputs are normalized by productive input I.[9] This yields the multi-output, input-oriented stochastic distance function

$$-\ln x_{nIt} = \beta_0 + \sum_i \beta_i \frac{\ln x_{nit}}{\ln x_{nIt}} + \sum_j \alpha_j \ln y_{njt} + \sum_k \delta_k \ln z_{nkt} + v_{nt} - u_{nt}$$

where u_{nt} denotes the distance to the efficient frontier (i.e., inefficiency) that is estimated along with α_j, β_i, and δ_k.[10]

Ultimately, the above model represents a *multiplicative, stochastic* framework, as it separates the random errors from inefficiency, and because the two stochastic terms are *multiplied* with

[6] E.g., see Bogetoft and Otto (2011, p.199 and p.218); for the formal derivation of estimate $\widehat{TE} = e^{-\hat{u}}$ refer to Bogetoft and Otto (2011, p.217).

[7] In this setting, the efficiency *ranking* across firms cannot change over time whereas $\eta = 0$ yields an estimation of time invariant inefficiency (Battese and Coelli 1992, p.154).

[8] See Bogetoft, 2012, p.126 or Bogetoft and Otto, 2011, p.236; for a single output, the output distance function is equivalent to the production function.

[9] Normalizing imposes the required homogeneity of degree 1 (e.g., Coelli and Perelman, 1996, p.9).

[10] In this respect, the institutional variables z do not change the properties of the error structure (cf. Coelli et al. 2005, p.285).

the production function. Thus, in contrast with additive fixed-effects settings, this setting expresses the inefficiency of each firm relative to the efficient frontier (i.e., to the feasible output given all inputs) rather than to the most efficient firm in the set. As a result, technical efficiency represents an absolute indicator with respect to the production technology rather than a purely comparative measure across firms (see Bogetoft and Otto, 2011, p.199 and p.217).

Data

Our dataset is based on the German Airport Project (GAP) database and our own Swiss Airports dataset, which we updated and complemented based on public financial statements, Eurostat and Swiss Federal Office of Statistics (BFS) data, and slot information from the European Airport Coordinators Association (EUACA). Thus, the consolidated dataset provides an unbalanced panel of 2000 to 2016 data for many German, Italian, French, and UK national and regional airports, the five Swiss airports under investigation, as well as some airports from other European countries. The data consist of total labor costs, overall input costs,[11] depreciation, physical runway capital, and airport outputs in terms of passenger and cargo volumes, air traffic movements, and revenues in annual terms. Moreover, the institutional data includes airport slot and ownership information. Based on the MCAR (missing completely at random)[12] assumptions, the imbalance does not affect the estimation.

We classify the airports into international airports that generate more than 2 million passengers per year and regional airports that generate less than 2 million passengers per year.[13] This classification is based on two arguments: Firstly, we suggest that the two types of airports differ in terms of their production functions, and secondly, it enables us to include non-aviation revenues and ownership data, which are available for the international airports but not for the regional airports. Additionally, the airports with less than 10 million passengers are sub-grouped by a dummy variable whereas, based on plausibility considerations, exceedingly small airports with less than 50'000 annual passengers are excluded as potential outliers. Similarly, exceptionally large hub airports are discarded for the surmise that their production function may substantially differ from that of the large international and smaller regional airports. The imbalanced dataset spans 16 time periods between the years of 2000 to 2015. For the international airports, we have 701 observations from 53 cross-sections; thus, the share of missing data is 18.9%. For the regional airports, we have 628 observations from 64 cross-sections with a missing data share of 38.6%.

Tovar and Martín-Cejas (2010, p.252) mention three problems with data in the airport efficiency context: The input choice, the output choice, and international data comparability. For the input & output choice, we are oriented toward the most recent studies in the literature but bound by data availability: Ideally, we would account for aviation and non-aviation related profits and costs, as particularly, large airports diversify their revenues to non-aviation activities (e.g., Tovar and Martin-Cejas, 2009, or Adler, Liebert, and Yazhemsky, 2013). Therefore, for the international airports, we measure aviation output in terms of total

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[11] In contrast with the EU28 cost data, which exclude ground handling, the Swiss regional airports provide fueling services on their own grounds; therefore, the fuel purchases are deducted from the overall input costs for these airports.

[12] MCAR means no attrition and no correlation with unobserved effects; cf., e.g., Baltagi (2013, p.189) or Kumbhakar and Lovell (2000, p.97).

[13] Generally, the critical passenger numbers are taken as the averages across all years.

passenger and cargo volumes[14] and the total number of air traffic movements (ATM), as well as by non-aviation revenues; for the regional airports, we measure aviation output only, as non-aviation revenues are only available for a few airports. Although this may induce unwarranted efficiency downgrades for the regional airports that diversify their business to non-aviation activities, we expect this distortion to be much less prominent than at large international airports so that we accept this limitation.

Table 2: Input Data Treatments

Input Cost	**Generic Price**	**Input Proxy***
Labor L	w_L^{DOM} : avg Labor Unit Costs per hour	$x_L = C_L^{DOM}/w_L^{DOM}$
Inputs I	PPP_{GDP} : PPP for Gross Domestic Product	$x_I^{EU28} = C_I^{DOM}/PPP_{GDP}$
Depreciation D	PPP for Capital Goods and Construction**	$D^{EU28} = D^{DOM}/PPP_{CAP}$
Revenues R	PPP_{GDP} : PPP for Gross Domestic Product	$R^{EU28} = R^{DOM}/PPP_{GDP}$

*EU28: Eurostat EU28 currency; DOM: domestic currency; ** PPP_{GDP} for 2000-2003 due availability

On the one hand, the international comparability of nominal costs obligates us to account for differences in the purchasing power across nations or regions. On the other hand, the evaluation of technical efficiency requires input *quantities*.[15] Therefore, we are obliged to perform some data treatments; firstly, to provide international comparability of costs and revenues, and secondly, to convert the costs into quantity proxies. For this purpose, the domestic labor costs C_L are transferred into labor work hours by applying the average hourly labor cost for production and services per country, as provided by Eurostat and BFS, as shown in Table 2.[16] Moreover, we convert input costs C_I and revenues R from domestic nominal expenses into real EU28 expenses based on Eurostat's Purchasing Power Parities for the Gross Domestic Product (PPP_{GDP}). Thus, presuming that, in real EU28 terms, the input prices are identical for all airports within both groups, these real EU28 expenses may also be interpreted as approximating input quantities. Lastly, as the airports' capital stocks are not readily available, we follow the usual practice in airport benchmarking by applying capital proxies. In this respect, we convert financial depreciation D by the PPP for Capital Goods and Construction (PPP_{CAP}) into a theoretical quasi-quantity for capital.[17] Moreover, as also usual in the literature, we approximate all airports' physical capital by their total runway length. As Tovar and Martín-Cejas (2010, p.253) mention, data treatments introduce potential scaling errors. However, in our case, they are required for international comparability.

[14] As usual in the literature, we accommodate the passenger and the cargo volumes into a single aggregate output where one work-load unit (WLU) corresponds to one passenger or 100 kg of cargo.
[15] However, among many, Battese and Coelli (1992) mix input costs and *quantities*.
[16] Hourly labor costs account for wages, salaries, as well as employers' social contributions and taxes; see Eurostat's NACE2 definition. For 2000-2008, production and services correspond to sectors C-K, which excludes public administration, whereas for 2009-2016, they are referred to as the business economy (Eurostat B-N). The missing years are linearly interpolated.
[17] Due to unavailability of PPP_{CAP} before 2004, we apply PPP_{GDP} for 2000-2003; as financial depreciation is not disclosed into air- and ground-side values, our depreciation measure includes both the operational air-side capital as well as the ground-side facilities.

Table 3: Correlations across input and output data for international and regional airports

	International Airports						
	L	**D**	**RL**	**I**	**WLU**	**ATM**	**NAR**
Labor (L)	1.000	0.647	0.437	0.636	0.696	0.619	0.685
Depreciation (D)	0.647	1.000	0.577	0.806	0.782	0.759	0.808
Runway Length (RL)	0.437	0.577	1.000	0.516	0.559	0.481	0.477
Other Inputs (I)	0.636	0.806	0.516	1.000	0.865	0.773	0.845
Output (WLU)	0.696	0.782	0.559	0.865	1.000	0.859	0.867
Output (ATM)	0.619	0.759	0.481	0.773	0.859	1.000	0.864
Non-aviation Revenues (NAR)	0.780	0.842	0.552	0.921	0.904	0.853	1.000
	Regional Airports						
	L	**D**	**RL**	**I**	**WLU**	**ATM**	**NAR**
Labor (L)	1.000	0.626	0.004	0.763	0.798	0.397	-
Depreciation (D)	0.626	1.000	0.043	0.648	0.635	0.342	-
Runway Length (RL)	0.004	0.043	1.000	0.074	0.226	-0.187	-
Other Inputs (I)	0.763	0.648	0.074	1.000	0.809	0.366	-
Output (WLU)	0.798	0.635	0.226	0.809	1.000	0.355	-
Output (ATM)	0.397	0.342	-0.187	0.366	0.355	1.000	-
-	-	-	-	-	-	-	-

As Table 3 shows, labor, other inputs, outputs in terms of WLU's and ATM's as well as non-aviation revenues (NAR) reasonably correlate. By contrast, for the international airports, runway length and depreciation highly correlate with the outputs and with labor and other inputs but only moderately correlate against each other. Although this indicates that a significant production function should be estimable, it also shows that the two capital proxies do not include the same information. For the regional airports, the runway length does not indicate a sensible correlation with any of the input and output data; this suggests that runway capital does not represent a reasonable proxy for the regional airports. In this respect, Adler et al. (2013, p.26) note that financial depreciation may not represent an ideal capital proxy due to differences in accounting standards across countries and investment cycles across airports. Therefore, we estimate two distinct distance functions for each group of airports: one with depreciation and one with physical runway capital as a capital proxy.

To control for exogenous sources of inefficiency, we introduce two institutional variables: airport ownership and slot coordination. *Airport ownership* refers to the degree of privatization by distinguishing full public ownership from a minority private share of less than 50% and a majority private share of more than 50%; again, unfortunately, the privatization data are only available for the international airports. *Slot coordination* denotes whether an airport is slot-coordinated and may take three values: slot constraints during all operating hours, during peak-period hours only, or a seasonal constraint during the summer or winter only. As slot information is available for the latest three seasons only, we extrapolate this information to all years. In addition, a year dummy controls for generalized annual shocks whereas a country dummy accounts for national differences.

Results

Our airport grouping signifies that we assume similar technologies *within* but heterogenous technologies *across* the two sets of airports; this leads us to estimate two separate stochastic frontiers rather than a joint one. Hence, the two international airport and the regional airport models are estimated based on Maximum Likelihood (ML) in a random effects setting (Coelli et al. 2005, p.278).[18] In terms of outputs, the international airport models include passenger and cargo volumes in terms of WLU's, air traffic volume (ATM), and non-aviation revenues (NAR) whereas the regional airport models are constrained to aviation outputs only (WLU's and ATM's). In terms of inputs, all models include labor and other inputs while we evaluate the production function with each of the two capital proxies for each group of airports.

The parameter estimates are shown in the appendix, where the ML estimation yields z-values with the corresponding p-values. The significances are indicated by *** for $p < 0.001$, ** for $p < 0.01$ and * for $p < 0.05$. In the distance functions, the coefficients represent elasticities rather than absolute values. Moreover, positive coefficients indicate a positive correlation between the variable at stake and the distance of the observation from the efficient frontier and, thus, inefficiency. By contrast, negative coefficients denote that inefficiency decreases (or: efficiency increases) when the corresponding variable increases (cf. Fernandez, Coto-Millan, and Diaz-Medina 2018, 55). Therefore, in a valid specification, inputs need to have positive coefficients and output negative coefficients. Similarly, institutional variables indicate inefficiency decrements if their sign is negative because they denote vertical shifts.

Firstly, the estimation results confirm the intuition in terms of the capital proxy and the heterogenous technologies: For the international airports, depreciation as a proxy renders the ATM output insignificant. Hence, we estimate model D.NAR based on depreciation and non-aviation revenues (NAR) only. By contrast, with runway length as a proxy, the non-aviation revenues become insignificant. Consequently, we estimate model RL.ATM based on physical runway capital and ATM's but without the NAR. As a result, we find one valid production function for each of the capital proxies but fail to estimate a model that jointly includes all three outputs. For the regional airports, the non-aviation revenues are not available. Moreover, physical runway length as a capital proxy fails to represent a significant productive input. As a result, only financial depreciation as a capital proxy yields an empirically valid model for the regional airports. As the correlation coefficients suggest, this result indicates that the characteristics of the capital stock may vary between the two groups of airports, which justifies the ex-ante assumption of heterogenous technologies.

As the results show, in all three valid models, we obtain the correct signs for the input and output coefficients, which means that higher inputs increase inefficiency whereas higher outputs decrease inefficiency. For the international airports, the input-labor elasticity in model D.NAR is both higher than depreciation as well as higher than in model RL.ATM. This shows that with depreciation as a capital proxy (in D.NAR), the the input-labor elasticity represents the main determinant of inefficiency whereas runway length dominates in the opposing case (RL.ATM). At the same time, the WLU's and the non-aeronautical revenues seem to both affect inefficiency in model D.NAR while, in model RL.ATM, both outputs seem relatively unimportant. In the regional airports model, both input elasticities are much lower whereas the passenger and cargo output returns a high importance as compared to the ATM's; moreover, as stated, physical runway length does not yield a significant production function at all. These insights illustrate the impact of the capital proxy choice on the efficiency measurement. Nonetheless, the likelihood ratios indicate that all SFA models exceed their OLS counterparts.

[18] We apply the statistical program 'R' and the software package 'frontier' due to Coelli and Henningsen (2017) for the estimation.

Thirdly, the institutional variables vary along with the different production functions: For the international airports in the RL.ATM model, all institutional variables are highly significant. They imply that inefficiency decreases at the same magnitude with both minor or major private ownership. In addition, all three types of slot coordination decrease inefficiency, and they do so to a higher degree than privatization. By contrast, in the D.NAR model, all significances are lost but for minority privatization and full-time slot coordination at the 5% level, whereas, the sub-class of airports with less than 10 million passengers are more efficient in the RL.ATM model but less efficient in the D.NAR model. For the regional airports, only full-time slot constraints are significant while the variations in all other institutional variables indicate that the model specification affects the estimation of the production technology to a large degree. The country variables show mixed significances throughout the set whereas the annual shocks are less important for the regional airports than for the international airports. These results may indicate that international airports face a higher exposure to international competition than regional airports. However, as the year and country dummies capture a multitude of generalized effects, they are difficult to interpret correctly.

In terms of inefficiency, the gamma values are extremely high for the regional airports and the RL.ATM model whereas random output variations are not observed. By contrast, in the D.NAR model they are lower, thereby indicating that four fifths of the variance stems from inefficiency and one fifth from random errors. Although Bogetoft (2012, pp.118) comments that small residuals indicate a strong model fit, we suggest that this result is extreme and might indicate that the D.NAR model for the international airports, which includes non-aviation revenues, provides a more realistic approximation of airport production than the regional airport and the RL.ATM models, both of which include outputs from aviation operations only. Concerning the time trends of inefficiency, for the regional airports, we observe a shallow but significant efficiency *increment* over time due to technology. By contrast, in both models of the international airports, the time trend indicates a minor but significant *decrement* of efficiency.

Although both international airport models are based on a rich set of output and institutional variables, we observe widespread rank changes between the two models, which result in a low Spearman's rank coefficient of 0.45. These rank reversions confirm that the efficiency scores largely depend on the input-output specifications, which includes the delicate choice of a suitable capital proxy. Thereby, we refer to Barros (2008) who also encounters widespread changes in his results with different model specifications. Since the two model outputs differ substantially, and since we cannot find a valid production function that accounts for all three kinds of outputs (passenger and cargo volumes, ATM's, and NAR), we refrain from publishing the efficiency scores.

Nonetheless, concerning the Swiss international airports, our SFA reports that Geneva yields constant high scores in both models whereas both Zurich and Basel seem to fare better in the non-aviation revenues model. In the runway length model (RL.ATM), Geneva's advantage might relate to its highly frequented single runway as compared to Basel's two and Zurich's three runways, where both airports exhibit a crossing runway configuration. This explanation also supports the latter two airports' relative efficiency increase in the depreciation and non-aviation revenues model (D.NAR), as both feature highly commercialized land-side areas. In addition, Geneva airport's location might result in a substantial share of cross-border commuting labor, so that we are likely to underestimate the labor input quantity and overestimate the technical efficiency when applying the Swiss national wage levels. As an opposite case, Basel airport is located on French territory but near Germany and Switzerland.

While we compute its units of labor with French wages, the salaries of cross-border employees might rather be determined by Swiss or German standards.

For the regional airports, we find that higher efficiency scores involve most larger airports and some small airports whereas lower efficiency scores mainly accommodate small airports. Tentatively, these results are likely to illustrate the problem of low airport demand for small regional airports. Contrastingly, the airports with difficult operational conditions due to topography such as Bern, Lugano, Bolzano, Florence, or Salzburg, are dispersed across the set although this precondition is not included as an institutional variable.[19] As the regional airport model contains aviation outputs but excludes non-aviation revenues as well as ownership information, we also refrain from publishing the regional airport efficiency ranking.

Conclusions

We benchmark the three international and two of the four main regional Swiss Airports against a representative set of 112 European airports based on a stochastic frontier analysis with an input-oriented, multi-output distance function. For the regional airports, the estimation yields a significant Cobb-Douglas production function with depreciation as a capital proxy and aviation outputs in terms of passenger and cargo volumes and air traffic movements. For the international airports, the production function is significant either with runway length and aviation outputs but without non-aviation revenues, or with financial depreciation and non-aviation revenues but without air traffic movements. Hence, we fail to estimate a single production function where capital (either in terms of physical runways or depreciation), air traffic movements, and non-aviation revenues are simultaneously significant.

Concerning the technical efficiency scores, the non-availability of non-aviation revenues and ownership information may underestimate the efficiency of regional airports who diversify their business models based on non-aviation activities and services, and who increase their efficiency by privatization. In the two international models, to some degree, the efficiency results may be explained by distinct physical capital bases, runway utilization, and cross-border effects within the labor force. However, many airports encounter substantial rank reversions across the two models, which results in a low spearman rank correlation. This indicates that the model specification - which includes the delicate choice of a suitable capital proxy - may substantially affect the efficiency scores. As a result, the explanatory power of our efficiency ranking remains severely limited.

Regarding the exogenous efficiency determinants, we investigate the impact of the institutional environment by accounting for the ownership of the airport and the degree of airport slot coordination. In this respect, the estimation indicates that efficiency is higher with privatization and with slot constraints. These results most closely relate to those of Adler et al. (2013) and Oum, Yan, and Yua (2008); however, they are not significant throughout all our three model specifications. In addition, the required data treatments for cross-country comparability, the unavailability of specific input prices, and the restrictive functional form of the production function limit the scope of the above efficiency results: Firstly, the applied country-level purchasing power parities might induce deviations from effective input prices.

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[19] All these airports only feature instrument approaches in one runway direction due to topography; depending on the cloud ceiling, visibility, and wind, this may induce severe operational constraints.

Secondly, the use of national wages does not account for domestic wage differentials between urban regions with high labor costs and non-urban regions with lower labor costs; similarly, airports in a multi-country catchment area might employ a significant share of their workforce at foreign rather than domestic wage levels. Moreover, the fact that several important institutional variables do not prove significant in all settings may indicate that other sources of inefficiency might remain hidden. For instance, the geographical or topographical location of an airport may create operational limitations that severely limit its potential output. Lastly, the chosen orientation of the distance function also affects the efficiency scores, as input-inefficient airports might become more efficient from an output maximization perspective.

With due consideration of the above limitations and a complementation with background information on the various sources of inefficiency, the study at hand might be of interest to policymakers, airport managers, and researchers who are interested in benchmarking operational infrastructures for the purpose of ameliorating their economic sustainability and operational performance. Nevertheless, subsequent studies may explore the partial insignificance of the institutional variables by evaluating different functional forms and by distinguishing discretionary from non-discretionary inputs, such as in Adler and Liebert (2014).[20] Moreover, an empirical estimation of appropriate factor prices would allow researchers to more precisely approximate input quantities, and evaluate cost and profit efficiency. However, such undertaking would require a rich dataset with detailed air- and land-side financial data that may be difficult to obtain.

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[20] For this purpose, Bogetoft (2012, p.29) proposes a sub-vector efficiency approach.

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Appendix: Stochastic Frontier Estimates

International Airports

	Model RL.ATM					Model D.NAR				
Parameter	Coeff	SE	z-Val	p-Val	Sig	Coeff	SE	z-Val	p-Val	Sig
(Intercept)	-7.738	0.319	-24.250	0.000	***	-7.607	0.553	-13.765	0.000	***
LN IL	0.102	0.011	9.037	0.000	***	0.695	0.021	33.694	0.000	***
LN CL	–	–	–	–		0.104	0.016	6.695	0.000	***
LN RLL	0.859	0.013	66.034	0.000	***	–	–	–	–	
LN Pax&Cargo	-0.058	0.016	-3.673	0.000	***	-0.379	0.035	-10.728	0.000	***
LN ATM	-0.043	0.016	-2.681	0.007	**	–	–	–	–	
LN NAR	–	–	–	–		-0.154	0.024	-6.489	0.000	***
factor(Belgium)	-0.130	0.501	-0.260	0.795		0.489	0.201	2.435	0.015	*
factor(Switzerl.)	0.515	0.268	1.917	0.055	.	0.493	0.127	3.889	0.000	***
factor(CzechRp)	-0.240	0.286	-0.838	0.402		-0.095	0.240	-0.396	0.692	
factor(Denmark)	0.827	0.268	3.087	0.002	**	0.981	0.158	6.205	0.000	***
factor(Estonia)	0.071	0.263	0.271	0.786		0.580	0.306	1.894	0.058	.
factor(France)	0.379	0.255	1.486	0.137		0.367	0.223	1.644	0.100	
factor(Germany)	1.258	0.281	4.474	0.000	***	0.512	0.145	3.528	0.000	***
factor(Greece)	-0.628	0.404	-1.556	0.120		0.507	0.305	1.664	0.096	.
factor(Hungary)	0.869	0.344	2.529	0.011	*	-1.443	0.208	-6.926	0.000	***
factor(Italy)	1.036	0.274	3.789	0.000	***	0.621	0.142	4.356	0.000	***
factor(Latvia)	0.124	0.273	0.454	0.650		1.296	0.361	3.592	0.000	***
factor(Malta)	0.509	0.395	1.288	0.198		0.503	0.146	3.446	0.001	***
factor(UK)	1.436	0.269	5.330	0.000	***	0.594	0.133	4.460	0.000	***
factor(2001)	-0.005	0.012	-0.412	0.680		-0.059	0.034	-1.772	0.076	.
factor(2002)	0.004	0.013	0.298	0.766		-0.074	0.034	-2.175	0.030	*
factor(2003)	-0.001	0.012	-0.068	0.946		-0.119	0.035	-3.342	0.001	***
factor(2004)	-0.004	0.013	-0.321	0.748		-0.182	0.038	-4.775	0.000	***
factor(2005)	-0.021	0.014	-1.552	0.121		-0.249	0.040	-6.196	0.000	***
factor(2006)	-0.020	0.014	-1.444	0.149		-0.248	0.042	-5.921	0.000	***
factor(2007)	-0.026	0.015	-1.719	0.086	.	-0.300	0.045	-6.694	0.000	***
factor(2008)	-0.033	0.016	-2.003	0.045	*	-0.370	0.048	-7.752	0.000	***
factor(2009)	-0.042	0.016	-2.594	0.009	**	-0.422	0.049	-8.680	0.000	***
factor(2010)	-0.051	0.017	-2.933	0.003	**	-0.495	0.052	-9.523	0.000	***
factor(2011)	-0.065	0.019	-3.474	0.001	***	-0.563	0.055	-10.311	0.000	***
factor(2012)	-0.064	0.019	-3.348	0.001	***	-0.609	0.058	-10.536	0.000	***
factor(2013)	-0.071	0.020	-3.596	0.000	***	-0.645	0.058	-11.100	0.000	***
factor(2014)	-0.057	0.021	-2.715	0.007	**	-0.644	0.060	-10.822	0.000	***
factor(2015)	-0.011	0.024	-0.452	0.651		-0.686	0.069	-9.980	0.000	***
factor(Priv<50)	-0.068	0.017	-3.896	0.000	***	-0.102	0.045	-2.273	0.023	*
factor(Priv>50)	-0.060	0.016	-3.728	0.000	***	-0.049	0.037	-1.330	0.184	
factor(SlotSeas)	-0.622	0.178	-3.501	0.000	***	-0.031	0.217	-0.145	0.885	
factor(SlotPeak)	-0.778	0.083	-9.389	0.000	***	-0.201	0.198	-1.013	0.311	
factor(SlotPerm)	-0.725	0.069	-10.434	0.000	***	-0.422	0.192	-2.201	0.028	*
factor(Pax10m)	-0.092	0.031	-2.969	0.003	**	0.225	0.064	3.507	0.000	***
sigmaSq	0.319	0.057	5.605	0.000	***	0.110	0.028	3.875	0.000	***
gamma	0.990	0.002	537.541	0.000	***	0.812	0.053	15.242	0.000	***
time	0.005	0.001	3.428	0.001	***	0.060	0.007	8.469	0.000	***

LR-Test	Df	LgLk	χ^2	p-Val	Sig	Df	LgLk	χ^2	p-Val	Sig
OLS	40	145.4	–	–		40	73.7	–	–	
SFA	42	879.8	1468.8	0.000	***	42	248.3	349.2	0.000	***

Regional Airports

Parameter	Coeff	SE	z-Val	p-Val	Sig	Parameter	Coeff	SE	z-Val	p-Val	Sig
(Intercept)	-6.931	0.530	-13.079	0.000	***	factor(2008)	-0.133	0.048	-2.793	0.005	**
LN_IL	0.189	0.021	9.153	0.000	***	factor(2009)	-0.105	0.050	-2.104	0.035	*
LN_CL	0.049	0.013	3.926	0.000	***	factor(2010)	-0.081	0.059	-1.376	0.169	
LN_Y	-0.401	0.020	-19.571	0.000	***	factor(2011)	-0.046	0.061	-0.764	0.445	
LN_ATM	-0.089	0.019	-4.771	0.000	***	factor(2012)	-0.022	0.064	-0.351	0.726	
factor(France)	1.696	0.431	3.933	0.000	***	factor(2013)	-0.075	0.066	-1.124	0.261	
factor(Germany)	0.028	0.418	0.068	0.946		factor(2014)	-0.056	0.069	-0.808	0.419	
factor(Italy)	1.300	0.435	2.989	0.003	**	factor(2015)	-0.036	0.115	-0.309	0.757	
factor(Slovenia)	-0.538	0.423	-1.271	0.204		factor (SlotSeas)	0.073	0.093	0.782	0.434	
factor(Switzerl.)	1.571	0.545	2.885	0.004	**	factor (SlotPeak)	0.072	0.131	0.546	0.585	
factor(UK)	0.855	0.432	1.977	0.048	*	factor (SlotPerm)	-1.275	0.293	-4.353	0.000	***
factor(2001)	-0.036	0.041	-0.890	0.373		sigmaSq	0.788	0.184	4.288	0.000	***
factor(2002)	-0.042	0.037	-1.117	0.264		gamma	0.971	0.007	133.609	0.000	***
factor(2003)	-0.049	0.038	-1.267	0.205		time	-0.022	0.006	-3.774	0.000	***
factor(2004)	-0.059	0.040	-1.483	0.138		—					
factor(2005)	-0.104	0.041	-2.527	0.012	*	**LR-Test**	**Df**	**LogL**	χ^2	**p-Val**	**Sig**
factor(2006)	-0.104	0.043	-2.395	0.017	*	OLS	30	127.58	–	–	
factor(2007)	-0.120	0.046	-2.629	0.009	**	SFA	32	163.39	581.9	0.000	***