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Airport Efficiency in Pakistan - A Data Envelopment Analysis with Weight Restrictions

By David Ennen*and Irem Batool†

This paper investigates the airports in Pakistan for potential cost inefficiencies. We identify inefficiencies by benchmarking the productive performance of airports using Data Envelopment Analysis (DEA). To improve the ability of DEA to differentiate performance levels, we analyze airport functions individually, using separate DEA models. In addition, restrictions are imposed on the possible weights of inputs and outputs in the DEA procedure, in order to improve the differentiation of performance. The definition of these weight restrictions is based on additional information on feasible production trade-offs and relative input prices. To the best of our knowledge, this paper provides the first application of predefined weight restrictions in a DEA analysis of airport efficiency. The results suggest that there are cost inefficiencies at several airports, which are mainly caused by overstaffing and overinvestment in capacity. Furthermore, we find that the operational scale of most airports is inefficiently small, so that increases in traffic will result in declining unit costs.
JEL: L93

I. Introduction

Competition between airports is often limited as there are several sources of market power (see e.g. Starkie, 2002). Moreover, airports that are potential rivals because of their spatial proximity sometimes have common ownership. This lack of competitive pressure may lead to inefficiencies in the provision of airport services. At state-owned airports, incentives for efficient operation can be particularly weak if losses may be covered by public funds. Therefore, performance benchmarking is an important tool for both public and private airport operators. Comparing the performance among airports helps in identifying excess use of resources and potential areas for improvement.

This paper investigates the airports in Pakistan for potential cost inefficiencies. In Pakistan, almost all commercial airports are fully state-owned. The only exception is the privately owned Sialkot International Airport, which was developed on a public-private partnership basis and started its operations in 2007.

To compare productive performance, practitioners in the industry generally use partial measures of performance (Francis et al., 2002). Partial performance measures, such as the number of passengers handled per employee, consider only selected inputs and outputs. However, comparisons based on partial performance measures may be misleading, if relevant inputs and outputs are ignored. For example, the indicator passengers per employee disregards activities that are not directly related to passenger handling, but are performed by employees, such as

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the facilitation of aircraft operations. Total performance measures take all inputs and outputs into account. Data Envelopment Analysis (DEA) is a technique that enables considering multiple inputs and outputs and is widely applied by academics to measure airport efficiency. DEA assigns each evaluated decision-making unit (DMU) a relative efficiency score ranging between zero and one, with one indicating efficiency. However, a common problem in DEA applications is that the performance of the DMUs cannot be differentiated sufficiently. DEA may rank most DMUs as efficient even though their performance differs. This is particularly likely to occur when the number of inputs and outputs is high in comparison to the number of observed DMUs.

We use DEA to identify potential inefficiencies at airports in Pakistan. To improve the differentiation of performance, we analyze airport functions individually, using separate models that include only the inputs and outputs directly related to each function. Thereby, the number of inputs and outputs in each model is reduced. In addition, we restrict the possible weights of inputs and outputs in the DEA procedure to further improve the differentiation of performance. These weight restrictions are defined on the basis of additional information on feasible production trade-offs and relative input prices. Kuosmanen and Post (2001) demonstrate that even a simple weight restriction can have a strong impact on DEA efficiency scores. For illustration, they assess the cost efficiency of commercial banks. From economic theory, they derive that equity capital should be a more expensive input for banks than debt capital, and therefore enforce a higher DEA weight for equity than for debt capital. To the best of our knowledge, predefined weight restrictions have not been incorporated into previous DEA analyses of airport efficiency.

Our results show that there are cost inefficiencies at airports in Pakistan. The inefficiencies found in the employment of labor have direct implications for airport management; increases in labor productivity are possible and would enable the reduction of staff numbers without changing the level of operation. In contrast, the inefficiencies identified in the use of capital cannot or can only minimally be decreased by management, as investments in airport infrastructure like runways and terminal buildings are irreversible. Only a significant growth in traffic in the future may better utilize existing capacity and increase efficiency. Thus, the measured capital efficiencies indicate rather where investment in airport infrastructure has been efficient in the past, and allow conclusions to be drawn on how future expansion plans should be designed. We also identify scale efficiencies and find that the operational scale of most airports is inefficiently small. Rising traffic levels would lead to a decline in unit costs at these airports, which has implications for airport charges and airport development.

Before turning to our analysis, we first discuss the DEA method, and factors that need to be considered in a DEA analysis of airport efficiency.

II. Measuring airport efficiency with DEA

Data Envelopment Analysis is a technique for measuring relative efficiency. In DEA, a production frontier is constructed from a set of comparable decision-making units and data on their input and output quantities. The efficiency of each DMU is defined by its relative distance from the production frontier. DEA is often used because of its attractive properties. That is, it is a non-parametric technique and therefore does not require assuming a parametric form of the production frontier. In addition, no information on input and output prices is needed.

In DEA analyses of airport efficiency, physical as well as financial measures of inputs and outputs are employed. Liebert and Niemeier (2010, 2013) review studies assessing the productivity and efficiency of airports. According to the list of DEA studies in Liebert and Niemeier (2010), commonly used inputs are the number of employees, number of runways, airport area, terminal area, staff costs, other operating costs and capital stock. Typically considered outputs are the number of passengers, number of aircraft movements, tonnes of cargo, aeronautical revenue and non-aeronautical revenue.

One of the main challenges in DEA is to ensure comparability between DMUs. Differences in the range and quality of inputs and outputs, factors not under the control of decision-makers, and variations in data-reporting methods complicate the analysis. To account for these circumstances, two strategies are pursued. First, the analysis can be restricted to a group of similar DMUs or to a comparable activity of DMUs. Second, dissimilarities can be allowed for in a DEA model, if suitable data are available to control for the respective factors. In the following, we discuss differences between airports and in airport data that are most challenging in benchmarking, and review some applications of the two approaches. In doing so, we also refer to studies that use other productivity measurement methods, but whose approach is transferable to DEA.

A. *Factors out of control of airport operators*

The transport demand at an airport is strongly influenced by population size and economic activity in the catchment area, and by nearby competing airports (Liu et al., 2006). The specific level of demand limits the influence of management on airport outputs like traffic volumes and revenues. One approach to accounting for this uncontrollable factor in DEA is to take outputs as given, by using the input-orientation and to measure outputs physically in terms of traffic numbers (see e.g. Pels et al., 2001). Thereby it is analyzed to what extent inputs, and therefore costs, could be reduced, while serving the same traffic volumes. Another procedure in DEA applied by Yu (2010) is to use the output-orientation in combination with a measure of demand as an uncontrollable input. In general, output-oriented DEA models evaluate to what extent outputs could be increased, while employing the same amount of inputs. Yu uses the population in the region surrounding the airport as a proxy for demand, and includes it as an uncontrollable input, which puts upper limits on the traffic numbers that efficient airports can achieve.

Demand also affects airport size, which has an impact on operating cost. There is considerable evidence that increasing economies of scale prevail at airports, at least to some point (see e.g. Tolofari et al., 1990; Pels et al., 2003; Martn and Voltes-Dorta, 2008). This means that airports with higher traffic volumes usually have lower unit costs. Average costs appear to decline most significantly up to a level of about three to five million passengers annually (Doganis and Thompson, 1973; Doganis et al., 1995; Main et al., 2003). In airport DEA studies, the variable returns to scale (VRS) model is often used, which was developed by Banker et al. (1984). The VRS model is an extension of the constant returns to scale (CRS) model introduced by Charnes et al. (1978). The shape of the production frontier of the VRS model incorporates the possibility that returns to scale increase at low output levels and decrease at high output levels. Thus, potential scale inefficiencies at smaller and larger airports are treated as beyond managerial control.

Furthermore, the type of passenger traffic depends on demand and affects the level of costs. A large share of international passengers results in higher unit costs, as more employees and terminal space are needed for immigration, customs and lounge areas (Graham, 2008, p. 77).

Besides demand, input prices also differ by geographical location, in particular wages and land prices. Therefore, instead of considering costs and asset values as inputs, physical measures such as the number of employees and the size of the airport area are often used in DEA applications (see e.g. Gillen and Lall, 1997).

Other factors that limit airport performance and are beyond the control of management include governmental noise regulations, such as restrictions on the number of aircraft movements and night curfews. In addition, climatic and topographic conditions of the airport location play a role. Strong winds from varying directions may require additional runways with different orientations. Snow falls necessitate snow removal and de-icing equipment and further personnel. High altitudes and high temperatures make longer runways necessary, because less dense air reduces the lift of aircraft wings and increases the required takeoff speed.

B. Factors under control of airport operators

The range of offered services belongs to the factors on which airport management can decide. Airport services can be classified as either aeronautical or non-aeronautical. Aeronautical activities are directly related to airport traffic and include the provision of runways, terminal buildings, air traffic control, security, fire services, and the handling of passengers, aircrafts and cargo. The non-aeronautical services of an airport include the granting of concessions for food and beverage outlets, retail shops, car parks, and car rentals, as well as the renting out of land, terminal area and advertising space. Different levels of involvement of airports in these activities make comparisons difficult. For example, at most airports worldwide, passenger, aircraft, and cargo handling is done by external handling agents or airlines. But some airports, particularly in Europe, offer handling services themselves and are in part heavily engaged in these activities (Graham, 2008, p. 73). Doganis et al. (1995) and the Transport Research Laboratory (TRL) (1999) account for diversity in the range of airport services by limiting their performance assessment to core aeronautical services that all studied airports provide exclusively by themselves. Non-core activities such as ground handling and non-aeronautical activities are excluded from the analysis. However, the restriction to core activities requires data on input usage broken down by airport activity, which may be unobtainable.

Moreover, the extent of certain activities may be negligibly small at some airports, but substantial at others. This applies particularly to non-aeronautical services. While some airports concentrate on the traditional aviation business, others have significantly developed the non-aeronautical sector. An omission of non-aeronautical activities could bias an analysis, if airports differ noticeably in this respect. The Air Transport Research Society (ATRS) (2003) calculates the variable factor productivity of major global airports and accounts for the non-aeronautical business by including the amount of non-aeronautical revenues as an airport output.

Different degrees of outsourcing constitutes another challenge, when evaluating airport efficiency or productivity. Labor input is typically measured as the number of employees or staff costs. But if services are bought in at some of the considered airports and are provided by airport employees at others, the amount of purchased services needs to be factored in for the purpose of comparability. In computing variable factor productivity, the ATRS (2003) uses the number of airport employees to measure labor input and a so-called soft-cost input to capture differences in outsourcing. The soft-cost input contains all expenses for bought-in materials and services like electricity, fuel, water, maintenance, repairs and consultancy.

Service quality may also vary considerably between airports. In particular runway congestion decreases service quality, as it leads to delays and increases costs of airlines and passengers. Airports with high capacity utilization experience low unit costs, but are usually characterized by above-average delay levels. Pathomsiri et al. (2008) analyze the performance of US airports using DEA, and account for different degrees of congestion by including the number of delayed flights and the average delay time as undesireable, but controllable outputs. Pathomsiri et al. employ delay data that contain only incidents which are most likely caused by the respective airport and not by extreme weather conditions, other airports or airlines.

C. Data comparability

Data comparability problems may arise, if capital and land input is measured by the book values of assets, because such values are based on historical costs and may be poor proxies of current market prices. In addition, accounting methods may differ between airport operators and countries. Therefore, instead of book values, physical measures of capital and land like the number of runways, the terminal area and the airport area are commonly used in DEA (see e.g. Gillen and Lall, 1997). Researchers who use the book values of assets in their analysis usually consider airports only in one country or airports of the same operator (see e.g. Martn and Romn, 2001).

D. Differentiation of airport performance

A general problem in Data Envelopment Analysis is a sufficient differentiation of the performance of DMUs. Most DMUs may be ranked as efficient even though their performance differs. This is especially likely when the number of observations is low relative to the number of inputs and outputs. The reason is the fact that DEA makes no a priori assumptions about the weights of inputs and outputs. If, for example, one DMU is really efficient in the usage of one input but not in others, the DMU may still receive the maximum efficiency score.

Podinovski and Thanassoulis (2007) review approaches to improving the differentiation of performance in DEA. One approach is to reduce the number of inputs and outputs. This can be achieved by aggregating some of the inputs and outputs or by ignoring less important ones. In airport DEA studies for example, the number of domestic and international passengers is often combined and treated as a single output. Another less restrictive approach that we follow in our analysis is the use of boundaries for input and output weights. These weight restrictions can, among other things, avoid that zero weight is assigned to some inputs and outputs.

In addition, in some cases, different parts or stages of a production process can be analyzed by separate DEA models. This reduces the number of inputs and outputs in each model and allows the further location of inefficient areas. Gillen and Lall (1997), for example, develop two separate DEA models for the airside and landside activities of airports. Yu (2010) furthermore describes airport operation as a multi-stage production process, using a slack-based measure network DEA approach. In the first stage of the production process, runway and terminal capacities are produced using capital and labor. These capacities are then employed as inputs in a second stage in order to service traffic.

The use of non-radial slack-based measure (SBM) models introduced by Tone (2001) is a further method for improving the differentiation of performance. Radial models such as the CRS or VRS model only identify possible proportional reductions in all inputs, or proportional increases in all outputs. Slack-based measure models enable determining further excesses or shortfalls in individual inputs or outputs. But without information on input prices, the efficiency scores obtained from input-oriented slack-based measure models have no cost interpretation.

In the following description of our DEA approach, we explain how we address the factors discussed in this section.

III. Methodology

This efficiency comparison is restricted to airports in Pakistan, in order to ensure a comparable regulatory and operating environment. We analyze cost efficiency and the associated scale efficiency. Output-oriented efficiency measures, in contrast, would require specifically accounting for differences in transport demand between airports. Therefore, we take output levels as given by using the input-orientation in DEA and measure outputs physically in terms of traffic numbers. Inputs are also measured in physical terms, because input prices like wages and land prices differ by location and book values of assets are, as explained, usually problematic.

We develop three DEA models to separately analyze the (1) runway system, (2) passenger terminals, and (3) employment of staff. Specifying separate models for different functions of airport inputs reduces the number of inputs and outputs in each model. This improves the differentiation of airport performance and enables the identification of more inefficiencies. Beyond that, areas of inefficiency can be located more accurately. It is possible to consider only part of the inputs in an input-oriented DEA model, when the included and excluded inputs are not substitutes for each other. The underlying assumption of our DEA models is that runway infrastructure, terminal infrastructure and labor are not substitutable, as also assumed by Pels et al. (2001). The physical layout and size of runways and terminals mostly determine their maximum handling capacities. The potential for the airport operator to trade off between infrastructure investment and labor input is very limited, if the airport is not directly involved in passenger, aircraft and cargo handling.

A. Cost-efficiency measure

Cost efficiency requires both technical and allocative efficiency. Technical efficiency implies the absence of input excesses. Allocative efficiency requires optimal input proportions given factor prices. Our approach is to determine upper bounds of cost efficiency using the non-decreasing returns to scale (NDRS) model. The NDRS model is a special variant of the VRS model and provides a measure of technical efficiency, if no additional price information is incorporated with the use weight restrictions. The radial measure of technical efficiency obtained from an input-oriented NDRS model indicates the extent to which all considered inputs can be reduced. The radial input-oriented measure of technical efficiency therefore represents an upper bound of cost efficiency (Russell, 1985).

The NDRS model allows for increasing returns to scale, just like the variable returns to scale (VRS) model. Thus, scale inefficiencies at small airports are taken into account and treated as beyond managerial control. In contrast to the VRS model, the NDRS model does not allow for decreasing returns to scale. Tolofari et al. (1990) and Martn and Voltes-Dorta (2008) find no diseconomies of scale in airport operation, even at some of the largest airports worldwide. Pels et al. (2003) find only slight evidence for decreasing scale economies. Starkie and Thompson (1985, p. 48-50) argue that decreasing economies of scale may exist if traffic levels are so high that separate passenger terminals are needed, spread over a wide area. In this case, remote satellite terminals need to be connected to the main terminal, requiring expensive infrastructure such as an underground transit system. As passenger volumes at all airports in Pakistan allow terminal operations to be centralized in a single building complex, the potential for considerable decreasing economies of scale seems negligible.

The description of the mathematical DEA procedure follows that in Cooper et al. (2007). Consider n airports and an airport function to be compared that involves the use of m different inputs to produce s different outputs. The input and output quantities of airport j $(j = 1, ..., n)$ are denoted by the input vector $\boldsymbol{x_j} = (x_{1j}, ..., x_{mj})^\top$ and the output vector $\boldsymbol{y_j} = (y_{1j}, ..., y_{sj})^\top$. The input and output quantities of all airports are described by the $m \times n$ input matrix $\boldsymbol{X} = (\boldsymbol{x_1}, ..., \boldsymbol{x_n})$ and the $s \times n$ output matrix $\boldsymbol{Y} = (\boldsymbol{y_1}, ..., \boldsymbol{y_n})$. To obtain efficiency scores under non-decreasing returns to scale (θ^*_{NDRS}), we solve for each airport o $(o = 1, .., n)$ the linear program

$$\begin{aligned}
&(1) \qquad && \underset{\boldsymbol{v},\boldsymbol{u},u_0}{max} \quad && \theta_{NDRS} = \boldsymbol{u}^\intercal \boldsymbol{y_o} - u_0 \\
&(2) && s.t. && \boldsymbol{v}^\intercal \boldsymbol{x_o} = 1 \\
&(3) && && \boldsymbol{u}^\intercal \boldsymbol{Y} - \boldsymbol{v}^\intercal \boldsymbol{X} - u_0 \boldsymbol{e} \leq \boldsymbol{0} \\
&(4) && && \boldsymbol{v} \geq \boldsymbol{0}, \quad \boldsymbol{u} \geq \boldsymbol{0} \\
&(5) && && u_0 \geq 0 \\
&(6) && && \boldsymbol{v}^\intercal \boldsymbol{P} \leq \boldsymbol{0} \\
&(7) && && \boldsymbol{u}^\intercal \boldsymbol{Q} \leq \boldsymbol{0},
\end{aligned}$$

where $\boldsymbol{v} = (v_1, ..., v_m)^\intercal$ is a vector of input weights, $\boldsymbol{u} = (u_1, ..., u_s)^\intercal$ is a vector of output weights, u_0 is a scalar, $\boldsymbol{e}$ is a $n \times 1$ vector of ones, $\boldsymbol{P}$ is a matrix of possible input weight constraints, and $\boldsymbol{Q}$ is a matrix of possible output weight constraints. The program for the standard VRS model is described by (1)-(4) with the sign of u_0 unrestricted. With the addition of the inequality (5) the VRS model becomes the NDRS model. The constraints (6)-(7) allow restricting the relative weights of inputs and outputs with the choice of the matrices $\boldsymbol{P}$ and $\boldsymbol{Q}$.

B. *Scale-efficiency measure*

We use the constant returns to scale (CRS) model to determine scale efficiency. The efficiency scores under constant returns to scale (θ^*_{CRS}) are obtained by solving for each airport o ($o = 1, .., n$) the linear program

$$\max_{\boldsymbol{v},\boldsymbol{u}} \quad \theta_{CRS} = \boldsymbol{u}^\intercal \boldsymbol{y_o} \tag{8}$$

$$s.t. \quad \boldsymbol{v}^\intercal \boldsymbol{x_o} = 1 \tag{9}$$

$$\boldsymbol{u}^\intercal \boldsymbol{Y} - \boldsymbol{v}^\intercal \boldsymbol{X} \leq \boldsymbol{0} \tag{10}$$

$$\boldsymbol{v} \geq \boldsymbol{0}, \quad \boldsymbol{u} \geq \boldsymbol{0} \tag{11}$$

$$\boldsymbol{v}^\intercal \boldsymbol{P} \leq \boldsymbol{0} \tag{12}$$

$$\boldsymbol{u}^\intercal \boldsymbol{Q} \leq \boldsymbol{0}. \tag{13}$$

The constraints (8)-(11) describe the standard CRS model and (12)-(13) represent possible weight restrictions. The ratio of CRS to NDRS efficiency ($\theta^*_{CRS}/\theta^*_{NDRS}$) yields the scale efficiency. A scale efficiency below one indicates that the scale of operation is inefficiently small and that there are economies of scale.

C. *Runway system model*

The runway system is evaluated using the total number of commercial and non-commercial aircraft movements as the single output. Accounting for non-commercial movements is important, as some airports share the runway system with an adjacent air force base, and military movements represent a significant share of total movements at these airports. Governmental restrictions that limit the time or the number of aircraft movements are not in place at any airport in Pakistan. The considered inputs are the number of runways and the number of taxiways running parallel to a runway for its full length. None of the airports has runways with different orientations, which implies that varying wind conditions do not determine the number of runways.

We impose two restrictions on the weights of the two inputs. The restrictions represent upper and lower bounds of the cost of runway construction relative to taxiway construction. Construction costs per square meter are similar for runway and taxiway surface. Full-length parallel taxiways are about half as wide as runways and their surface area including connectors is between half and the total runway area. Thus, the construction costs of a parallel taxiway should amount to somewhere between half and the total costs of a runway. This leads to the following two restrictions. First, the taxiway weight (v_2) must be at least half the runway weight (v_1): $0.5v_1 - v_2 \leq 0$. Second, the taxiway weight should not exceed the runway weight: $-v_1 + v_2 \leq 0$. In matrix notation, the input weight restrictions can be written as

$$\boldsymbol{v}^\intercal \boldsymbol{P} = \begin{pmatrix} v_1 & v_2 \end{pmatrix} \begin{pmatrix} 0.5 & -1 \\ -1 & 1 \end{pmatrix} \leq \begin{pmatrix} 0 \\ 0 \end{pmatrix}. \tag{14}$$

The addition of weight restrictions based on input prices changes the meaning of efficiency scores. The efficiency scores no longer indicate technical efficiency, but solely represent upper bounds of cost efficiency (Camanho and Dyson, 2005).

Delays that result from shortages in runway capacity cannot be accounted for in the model itself, because there is no such detailed delay data for Pakistan. To avoid comparing severely congested airports, where runway capacity may be inefficiently low, to uncongested airports, we exclude congested airports from the runway model based on assessments of officials from the Civil Aviation Authority Pakistan (CAA).

D. Passenger terminal model

The second model analyzes the passenger terminal buildings. Terminal size, measured in square meters of floor space, is used as the single input and the number of domestic passengers and the number of international passengers as the outputs. We define two restrictions for the output weights of the two passenger types. The restrictions represent the trade-off between possible uses of floor space. More terminal space is generally needed to handle international passengers. Ashford et al. (2011, p. 430) gives typical space requirements per peak-hour passenger of 14 square meters for domestic terminals and 24 square meters for international terminals, which implies a 71% larger area requirement. We conclude that the terminal space needed for international passengers should amount to between the same and twice the space required for domestic passengers. This results in the following two restrictions. First, the output weight of international passengers (u_2) must be at least the output weight of domestic passengers (u_1): $u_1 - u_2 \leq 0$. Second, the output weight of international passengers should not exceed twice the output weight of domestic passengers: $-2u_1 + u_2 \leq 0$. In matrix notation, the output weight restrictions can be written as

$$\boldsymbol{u}^\intercal \boldsymbol{Q} = \begin{pmatrix} u_1 & u_2 \end{pmatrix} \begin{pmatrix} 1 & -2 \\ -1 & 1 \end{pmatrix} \leq \begin{pmatrix} 0 \\ 0 \end{pmatrix}. \tag{15}$$

The addition of weight restrictions reflecting feasible production trade-offs does not change the meaning of the efficiency scores (Podinovski, 2004). The interpretation as technical efficiency remains. Because we consider only one input in the terminal model, allocative inefficiencies in the choice of inputs cannot exist. Thus, the obtained efficiency scores indicate not only technical, but also cost efficiency, irrespective of input prices.

The airports rent out part of the terminal space to other businesses, but this non-aeronautical activity is of minor importance in Pakistan. According to the CAA annual report 2012, only about 14% of total revenue of all state-owned airports are earned in the non-aeronautical sector. Thus, we assume that each airport uses the same large share of terminal space for aeronautical purposes and do not consider non-aeronautical activities.

E. Staff model

The employment of airport staff is evaluated by the third model. At all considered Pakistani airports, the function of airport personnel is limited to facilitation and regulation. The processing of passengers, aircrafts and cargo is done by handling agents, airlines and shippers. Other federal employees working at the airport provide custom and immigration services, security controls and protection of the premises. In the model, the number of airport employees is considered as the single input and the number of passengers, tonnes of cargo and number of commercial aircraft movements as the outputs. We do not include other federal employees working at the airport in the model, because security requirements differ substantially between airports in Pakistan. In particular, the airports Peshawar and Quetta are located close to areas with a presence of terrorist groups and therefore employ considerably more security personnel. As security requirements are beyond control of the airport operators, and further segregated data on staff is unobtainable, we ignore all other federal employees, including the Airport Security Force as well as customs and immigration officers. Since most of the additional work in handling international passengers is related to customs and immigration, and the personnel of these two departments is excluded, we do not treat domestic and international passengers as two separate outputs with potentially different costs in the airport staff model.

The airports buy-in some services rather than employing their own personnel, but this applies only to a few specific services. According to the CAA annual report 2012, at 78.2% salaries and other personnel-related expenses account for the majority of total non-capital expenses of all state-owned airports.[1] Cost items including labor from third parties such as repairs and maintenance, legal and professional, and horticulture, together make up only 4.5% of total non-capital expenses. We therefore ignore potential differences in outsourcing between airports.

As in the terminal model, we consider only one input in the staff model. Similarly, allocative inefficiencies cannot exist and the obtained efficiency scores indicate technical as well as cost efficiency.

Finally, inputs, outputs, and efficiency measures of all three models are summarized in Table 1. Weight restrictions are summarized in Table 2.

Table 1—DEA models

Model	Efficiency measures	Inputs	Outputs
1. Runway system	CE = θ^*_{NDRS} SE = $\theta^*_{CRS}/\theta^*_{NDRS}$	(1) Runways (2) Taxiways	(1) Total aircraft movements
2. Passenger terminal	CE = TE = θ^*_{NDRS} SE = $\theta^*_{CRS}/\theta^*_{NDRS}$	(1) Terminal size (in m^2)	(1) Domestic passengers (2) International passengers
3. Staff	CE = TE = θ^*_{NDRS} SE = $\theta^*_{CRS}/\theta^*_{NDRS}$	(1) Employees	(1) Total passengers (2) Commercial aircraft movements (3) Cargo and mail (in tonnes)

Note: CE, cost efficiency; SE, scale efficiency; TE, technical efficiency.

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[1] Total non-capital expenses are calculated as general and administrative expenses minus depreciation, amortization, provision for doubtful debts and provision for doubtful other receivables.

Table 2—Weight restrictions in DEA models

Model	Restrictions on input weights (v_i) and output weights (u_j)
1. Runway system	(1) $-v_1[Runways] + v_2[Taxiways] \leq 0$
	(2) $0.5 \cdot v_1[Runways] - v_2[Taxiways] \leq 0$
2. Passenger terminal	(1) $u_1[Dom.\ Pass.] - u_2[Int.\ Pass.] \leq 0$
	(2) $-2 \cdot u_1[Dom.\ Pass.] + u_2[Int.\ Pass.] \leq 0$

IV. Data

The primary data source is the Civil Aviation Authority Pakistan (CAA). Information on passengers, aircraft movements and cargo are extracted for the financial year 2011-12 from the publicly available aviation statistics. The number of employees at each airport was provided by the CAA on request, for all commercial airports in Pakistan with more than 50,000 passengers per year.

Data on terminal size are not publicly available for all airports. Thus, we use the software Google Earth Pro to determine the passenger terminal footprints with the help of satellite pictures. In combination with information on the number of floors of the terminal buildings, we approximate the terminal size. For some airports, information on passenger terminal size is available on the airport website. A comparison between the stated and estimated terminal sizes shows that the method is quite accurate with maximum deviations of less than 5%.

The resulting dataset consists of 12 airports, of which selected characteristics are shown in Table 3. The three largest airports, namely, Karachi, Lahore and Islamabad, have between 3 and 6 million passengers per year. Bahawalpur, Rahim Yar Khan and Turbat are comparatively tiny, with far less than 100,000 annual passengers and on average, less than 5 commercial aircraft movements per day.

According to CAA officials, runway congestion is a major problem at Islamabad. The airport is the second largest in Pakistan in terms of aircraft movements, but

Table 3—Airport characteristics in 2011-12

Airport	Runways	Parallel taxiways	Terminal size (in m^2)	Passengers	Aircraft movements
Bahwalpur	1	0	1,446	53,780	2,662
Faisalabad	1	1	4,823	135,737	1,753
Islamabad	1	0	33,874	3,612,178	37,236
Karachi	2	1	110,756	5,968,531	52,556
Lahore	2	1	80,324	3,680,436	31,316
Multan	1	1	3,076	228,312	26,676
Peshawar	1	0	12,987	1,300,948	10,341
Quetta	1	0	8,760	321,977	4,421
R. Y. Khan	1	0	2,712	52,490	1,888
Sialkot	1	0	8,316	254,859	2,767
Sukkur	1	1	3,376	97,602	2,499
Turbat	1	0	1,253	50,153	1,526

has only a single runway and no parallel taxiway, which limits runway capacity substantially. As the estimated benefits of a planned taxiway exceed by far the projected cost,[2] we conclude that runway capacity at Islamabad is inefficiently low, and therefore exclude the airport from the runway model.

While Islamabad, Quetta and Peshawar share their infrastructure with adjoining airforce bases, an army base is located at Multan airport, where numerous attack helicopters are stationed. Helicopter movements appear to constitute a significant share of total aircraft movements at Multan. As helicopters do not contribute to runway utilization, and data on airplane rather than aircraft movements is not available, we ignore also Multan in the runway system model.

V. Results

A. *Runway system efficiency*

The results of the runway system model are reported in Table 4. All airports with a single runway and no parallel taxiway have a cost-efficient runway system. Their infrastructure is absolutely essential for handling any airplane traffic, implying technical as well as cost efficiency. The runway system at Faisalabad and Sukkur is found to be cost-inefficient. Both airports have a single runway and a single taxiway, which allows the conclusion that their taxiways are not needed for the entire length, at least not at current traffic levels. Cost inefficiencies identified at Lahore could at least in part stem from the size of the runway system. The airport has two runways and one full-length taxiway like the cost-efficient Karachi airport, but serves 40% fewer aircraft movements.

Table 4—Runway system efficiency

Airport	Cost efficiency	Scale efficiency	Economies of scale
Bahawalpur	1.000	0.152	Increasing
Faisalabad	0.667	0.083	Increasing
Karachi	1.000	1.000	Constant
Lahore	0.698	0.854	Increasing
Peshawar	1.000	0.590	Increasing
Quetta	1.000	0.252	Increasing
R. Y. Khan	1.000	0.108	Increasing
Sialkot	1.000	0.158	Increasing
Sukkur	0.667	0.119	Increasing
Turbat	1.000	0.087	Increasing

Note: Islamabad and Multan are excluded.

Increasing economies of scale in runway operation are identified at all airports except Karachi, implying the existence of considerable scale economies. Karachi, the largest airport in Pakistan with 6 million passenger in 2011-12, is scale efficient

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[2] In 2015, the construction of a taxiway was completed at Islamabad airport. Officials argued that the taxiway would reduce aircraft waiting times to the levels at Lahore and Karachi. The construction costs of the taxiway of 200 million Pakistani rupees stand in contrast to estimated savings by airlines alone of about 1.4 billion rupees per year (Klasra, 2015).

and Lahore, the second largest with 3.7 million passengers, operates close to scale efficiency as indicated by a score of 0.85. At the smallest airports measured by aircraft movements, Faisalabad, Rahim Yar Khan and Turbat, scale inefficiencies are most pronounced and suggest low runway utilization.

From a theoretical point of view, scale economies in runway operation are caused by indivisibilities in the provision of takeoff and landing capacities. To deal with any air traffic at all, an airport obviously requires a runway involving a large initial investment. With growing traffic levels, runway utilization rises, and average costs drop until congestion becomes a problem. Therefore, we would expect scale economies already to be exhausted at airports with a single runway, given that traffic volumes are sufficiently large. Our result that only Karachi, an airport with two runways, is fully scale efficient, may be driven by the fact that we do not observe many different traffic levels, and exclude the single runway Islamabad airport because of congestion problems.

B. Passenger terminal efficiency

Table 5 displays the results of the passenger terminal model. The cost efficiency of passenger terminals is determined by their technical efficiency. We find technical inefficiencies at several airports, indicating that either terminal capacity is larger than actually needed or that building design is inefficient, thus not allowing a higher number of passengers. To some degree, the identified inefficiencies probably represent unavoidable underutilization of terminal capacity. Airports can extend terminals only in phases, which typically results in unused capacity after completion of an extension project. However, indivisibilities in the provision of terminal capacity should be significantly smaller than in the provision of runway capacity.

Table 5—Passenger terminal efficiency

Airport	Cost efficiency (Technical efficiency)	Scale efficiency	Economies of scale
Bahawalpur	0.890	0.392	Increasing
Faisalabad	0.422	0.625	Increasing
Islamabad	1.000	1.000	Constant
Karachi	0.505	1.000	Constant
Lahore	0.435	1.000	Constant
Multan	0.938	0.742	Increasing
Peshawar	1.000	1.000	Constant
Quetta	0.427	0.807	Increasing
R. Y. Khan	0.470	0.386	Increasing
Sialkot	0.391	0.779	Increasing
Sukkur	0.500	0.542	Increasing
Turbat	1.000	0.375	Increasing

Increasing economies of scale are identified at airports with up to 350,000 passengers annually. Scale inefficiencies are largest at Bahawalpur, Rahim Yar Khan and Turbat, all with less than 100,000 passengers per year. The reason for these scale economies may be that peak hour terminal capacity needs to be comparatively large at small airports. Because of economies of aircraft size, airlines have a preference for operating large aircraft. This generally leads to variations in demand for terminal capacity during the course of the day, which is especially pronounced at airports where total passenger volume is low. At the smallest airports in Pakistan, capacity is used only a few times a day, resulting in low average utilization.

C. *Staff efficiency*

The results of the staff model are shown in Table 6. Cost efficiency is again determined by technical efficiency. The highest technical inefficiencies are identified at Faisalabad, Peshawar, Rahim Yar Khan and in particular Quetta. The airports employ too many staff, given their traffic levels. Efficient staff levels are found at the private Sialkot airport and the public Karachi, Multan and Turbat airports. The cost figures in the CAA annual report 2012 provide additional evidence of the generally low labor-cost efficiency. Salaries and other personnel-related expenses account for 61% of total expenses of all state-owned airports.[3] In contrast, the share of labor costs ranges between 15% and 50% at most airports worldwide (Graham, 2008, pp. 74-76). Iftikhar (2015) cites political motives and improper corporate governance as causes of excessive employment at many public enterprises in Pakistan.

TABLE 6—STAFF EFFICIENCY

Airport	Cost efficiency (Technical efficiency)	Scale efficiency	Economies of scale
Bahawalpur	0.484	0.510	Increasing
Faisalabad	0.351	0.591	Increasing
Islamabad	0.539	1.000	Constant
Karachi	1.000	1.000	Constant
Lahore	0.899	1.000	Constant
Multan	1.000	1.000	Constant
Peshawar	0.322	1.000	Constant
Quetta	0.158	1.000	Constant
R. Y. Khan	0.293	0.475	Increasing
Sialkot	1.000	1.000	Constant
Sukkur	0.609	0.861	Increasing
Turbat	1.000	0.682	Increasing

Economies of scale appear to be very limited in the activities performed by employees. The results indicate that only tiny airports with less than 150,000 passengers per year exhibit increasing economies of scale. A possible explanation for these scale economies is that personnel at smaller airports is more often idle for two reasons. First, a certain number of employees with different qualifications is

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[3] Total expenses are calculated as general and administrative expenses minus provision for doubtful debts and provision for doubtful other receivables.

needed to run an airport, which limits the potential to reduce labor input. Second, strong variations in traffic volumes during the course of the day are more difficult to match with appropriate staff numbers, and can result in longer employee idle times. But in contrast to terminal capacity, labor input can be matched to some extent with varying traffic levels, for example by reducing operating times of an airport. This could explain why scale economies in labor are found to be comparatively small.

VI. Conclusions

Data Envelopment Analysis is often applied to determine the relative efficiency of airports. The use of weight restrictions and a separate analysis of airport functions can improve the ability of DEA to differentiate between the levels of efficiency. By applying this approach, we are able to identify significant cost inefficiencies at airports in Pakistan, although we benchmark a comparatively low number of airports.

We find that inefficiencies exist in the infrastructure of some airports, which are in part a result of overinvestment in capacity in the past. Basing the capacity of new airports and expansion projects more strongly on short-to-medium-term traffic needs could avoid such inefficiencies in the future. The staff efficiency results suggest that there is room for improving labor productivity at several airports, which would allow for reduced staff.

In addition, we find that most airports in Pakistan operate under increasing economies of scale, which implies that rising traffic would lower unit costs. That the operational scale of many airports is inefficiently small has implications for airport charges and airport development. Instead of investing in capacity at large, busy airports, nearby underutilized airports could play a greater role as reliever airports. To achieve this, the CAA could differentiate charges between airports more strongly. Higher charges at congested airports would create incentives to shift traffic to underutilized airports. Furthermore, the construction of new airports in the vicinity of scale-inefficient ones may lead to unnecessary cost duplication.

Our disaggregated approach also gives some indication as to the source of scale economies in airport operation. While scale economies in passenger terminal throughput and in airport staff activities appear to be exhausted at comparatively low traffic levels, the runway system is found to be an important driver of scale economies. Economies of scale in runway operation can be explained by substantial indivisibilities in the provision of starting and landing capacities.

This efficiency analysis excludes airports that may well be congested, from the runway system evaluation. Detailed data on aircraft delays would allow for a further DEA analysis, which includes all airports and takes capacity-related aircraft delays, as an undesirable airport output, into account.

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