Efficiency Measurement for Airports

Research Associate, Torben Holvad
Transport Studies Unit, University of Oxford

Senior Lecturer Anne Graham

Transport Studies Group, University of Westminster

1. Introduction

Economic performance of European and Australian airports have been examined in a joint research project by University of Westminster and Cranfield University, see Doganis et al (1994). The performance analysis was based on a comparison of a range of productivity measures. This paper will supplement those findings by examining the relative efficiency for the same airports with the same data but utilise other methods, Data Envelopment Analysis (DEA) and Free Disposal Hull Analysis (FDH). The application of different performance measurement methods on the same data set can be seen as a way to test the robustness of the performance results. If performance results with different methods are similar then it is an indication that the findings have revealed a general property of the data and are not caused by the specific method used. Obviously, this is only a necessary condition and not a sufficient condition for the generality of the results. DEA and FDH belong to the so-called non-parametric approach to the measurement of efficiency. Efficiency measurement methods within the non-parametric approach are characterised by not assuming a functional form for the relationship between the inputs and outputs. These methods can include multiple inputs and multiple outputs without the need to weigh the inputs and outputs in order to form composite input and output measures. In this way, these methods are well suited to be applied in the context of airports. FDH and in particular DEA have in recent years been applied to a wide range of sectors including transport, see e.g. Oum and Yu (1994) and Försund (1992). However, within the airport sector transport there have only been a few applications, see e.g. Salazar de la Cruz (1999) and Murillo-Melchor (1999). Thus, the present paper represents a possibility to gain further insight into the potential to use DEA and FDH within the airport sector.

The plan for the paper is as follows. In section 2 DEA and FDH are briefly reviewed. Section 3 describes the airport data in terms of inputs and outputs used. The efficiency results are presented in section 4 focussing on the comparison between European and Australian airports. Section 5 concludes in final remarks.

2. Methodology

Data Envelopment Analysis (DEA) and Free Disposal Hull Analysis (FDH) examine the efficiency of similar production units using so-called dominance comparisons of the units' inputs and outputs. Each production unit is compared to the whole sample of production units in order to determine whether there exist other production units (or combination of production units) using the same or less of the inputs to produce the same or more of the outputs. If this is the case, the production unit is termed inefficient. Otherwise, the production unit is efficient. In this way the efficiency concept is a relative one as it is only concerned with efficiency in relation to the sample and not some absolute efficiency standard.

Formally, assume there are n production units (indexed as k=1,...,n) using m inputs (indexed as j=1,...,m) to produce s outputs (indexed as i=1,...,s). The k'th production unit can now be described by the production vector (X_k,Y_k) where X_k $(X_k=(x_{k1},...,x_{kj},...,x_{km}))$ is the input vector and Y_k $(Y_k=(y_{k1},...,y_{ki},...,y_{ks}))$ is the output vector. Consider the dominance comparison for production unit k0[1]. DEA compares k0 to linear combinations of the n production units, i.e. $(\Sigma_k 8_k X_k, \Sigma_k 8_k Y_k)$ with $8_k \geq 0$[2]. Therefore, k0 is dominated in terms of inputs if $\Sigma_k 8_k x_{kj} \leq x_{k0j}$ holds for all inputs with strict inequality for at least one input and $\Sigma_k 8_k y_{ki} \geq y_{k0i}$ is satisfied for all outputs for at least one combination of production units. Similarly, if $\Sigma_k 8_k x_{kj} \leq x_{k0j}$ for all inputs and $\Sigma_k 8_k y_{ki} \geq y_{k0i}$ for all outputs with strict inequality for at least one output for at least one combination of production units, k0 is dominated in terms of outputs. Dominated production units are inefficient while undominated ones are efficient. Free Disposal Hull Analysis (FDH) restricts the dominance comparison for k0 to be with respect to other production units, i.e. FDH excludes linear combinations of production units from the analysis. Keeping the previous notation, FDH compares (X_{k0}, Y_{k0}) to $(\Sigma_k 8_k X_k, \Sigma_k 8_k Y_k)$ where $8_k \in \{0,1\}$ and $\Sigma_k 8_k = 1$. The definition of dominance is as before, but the added restrictions on 8_k imply that it is less likely for a production unit to be dominated, i.e. inefficient.

[1] k0 belongs to the sample of n production units.

[2] This corresponds to a DEA model with constant returns to scale. Other DEA models are available which introduce an additional restriction concerning $\Sigma_k 8_k$. A DEA model with non-increasing returns to scale is obtained if $\Sigma_k 8_k \leq 1$ while a DEA model with variable returns to scale is formulated by restricting 8_k to be such that $\Sigma_k 8_k = 1$ holds.

Thus, DEA and FDH can serve to partition a set of production units in two subsets: (a) efficient production units and (b) inefficient production units. Additional information about the inefficient production units' deviation from efficiency can also be derived using DEA or FDH. Two types of measures for the extent of efficiency for a given production unit can be calculated: (a) output efficiency measures and (b) input efficiency measures. The input efficiency measure compares the actual input level to the best practice input level (defined as the combination of production units that dominate k0. Similarly, the output efficiency measure relates the actual output level to the potential output level. An input efficiency measure for k0 can be calculated as follows: For each dominating combination of production units, $(\Sigma_k 8_k X_k, \Sigma_k 8_k Y_k)$, compute the input ratios $(\Sigma_k 8_k x_{kj}) / x_{k0j}$. The smallest of these ratios $((\Sigma_k 8_k x_{kj}) / x_{k0j})^*$ which satisfies

$$\Sigma_k 8_k x_{kj} \leq ((\Sigma_k 8_k x_{kj}) / x_{k0j})^* \cdot x_{k0j}$$

for all inputs is chosen as the input efficiency measure. The input efficiency measure will take values in the range from zero to 1 with inefficient production units having values below 1. A necessary condition for a production unit to be input efficient is that the input efficiency measure is equal to 1. A sufficient condition for input efficiency would require that

$$\Sigma_k 8_k x_{kj} = ((\Sigma_k 8_k x_{kj}) / x_{k0j})^* \cdot x_{k0j}$$

holds for all inputs. This problem is caused by the way the efficiency measure is calculated: it measures the proportionate reduction in the inputs a production unit should undertake in order to become efficient. However, after reducing all inputs proportionately further reductions for some inputs might be possible. In a similar way an output efficiency measure can be derived for k0, but the details will not be included in this paper, see e.g. Fried et al. (1993).

The calculation of input and output efficiency measures can for both DEA and FDH be formulated as mathematical programming problems, see e.g. Fried et al. (1993) for an overview. An important aspect of DEA is the possibility to decompose inefficiency into pure technical inefficiency and scale inefficiency (operating on a non-optimal scale), see e.g. Banker (1984).

A number of advantages of DEA and FDH analysis can be listed. One main advantage is that no functional form regarding the relation between inputs and outputs is necessary in order to compute the efficiency measures. Secondly, the techniques allow for multiple inputs and multiple outputs without the use of weighting factors. In this way a more valid model of production activities is provided. This implies that DEA/FDH can be applied in situations where inputs and/or outputs are measured in physical units. Moreover, the efficiency concept is weak since it allows for observations being efficient if they are specialising, so if inefficiency is detected with DEA or FDH it is difficult to ignore. Finally, the DEA/FDH techniques are consistent with the production theoretic concept of efficiency as these are based on the maximum output for given input levels. However, DEA and FDH have also disadvantages where some of these are specific to these methods and others are present with other performance measurement techniques. Firstly, it is assumed that it is possible to define and measure a set of inputs and outputs for each production unit and that these characterise the production activities. Related to the input-output specification is the issue of similarity. It is important that the production units included are similar in the sense that they can be described by identical input and output categories. Otherwise, observations can be defined as efficient due to a special output/input profile, which would imply meaningless results from the analysis. This problem is parallel to the problems of outliers. Production units with an extreme production structure (e.g. specialisation into a single output) may be defined as efficient simply because of the special production structure. The problems of non-similarity and outlier influence can imply that it is not possible to achieve a complete ranking of the production units because relative many will be characterised as efficient. In general, there is a trade-off between a realistic description of the production profile and a complete ranking. If the efficiency analysis is based on a few number of variables then it is likely that a complete ranking can be obtained but restricting the number of variables to describe the production might not give a realistic impression of the production activities. On the other hand, inclusion of many variables will provide a more reliable description of the production activities, but this increases the possibility for specialisation and therefore makes a complete ranking less likely. This problem has been addressed in two recent studies. In Olesen & Petersen (1993) a test is developed that determines the optimal number of variables to include in a DEA analysis. Kittelsen (1992) suggests a procedure that can establish a statistical optimal data specification.

3. Data

The efficiency analysis is based on data for 25 European and 12 Australian airports. 1993 data are used for most European airports[3] while 1992-93 data are used for Australian airports (year ending June 1993). A range of activity information has been collected for each of these airports including financial data on costs, revenues and profits. The data have been adjusted for differences due to special production conditions in order to obtain a comparable sample.

For the present efficiency analysis the following inputs and outputs have been specified:

Input (1)	Employees (measured in number of full-time employed)
Input (2)	Capital Costs (measured in Australian $)
Input (3)	Other Costs (measured in Australian $)
Output (1)	Terminal Passengers (measured in number of persons)
Output (2)	Cargo (measured in tonnes)

[3] However, data for UK airports are based on either the year ending March 1993 (Cardiff, East Midlands, Manchester and Newcastle) or the year ending March 1994 (Birmingham, London Heathrow and Gatwick, Glasgow).

In Doganis, Lobbenberg & Graham (1994) further details on the airport data are included. Table 1 shows summary statistics of the input-output data for the European and Australian airports.

Table 1. Summary Statistics for Data for European and Australian airports

	Employees (Full-time employed)	Capital Costs (Mill A$)	Other Costs (Mill A$)	Terminal Passengers (Mill)	Cargo (Th Ton.)
Average Eu	777	45.9	56.4	10.6	186.2
Average Au	133	13.3	5.7	3.9	59.3
Standard Dev. Eu	757	58.2	81.2	10.9	330.7
Standard Dev. Au	128.5	17.3	7.1	5.0	97.9
Median Eu	591	27.8	26.6	7.0	65.3
Median Au	62.5	6.1	1.9	1.5	7.9
Maximum Eu	2957	276.4	344.0	48.4	1301.1
Maximum Au	442	61.4	25.3	16.4	320.3
Minimum Eu	86	2.3	1.0	0.4	0.9
Minimum Au	36	1.9	1.1	0.5	1.75

4. Results

This section will examine the efficiency variations for the included airports from a range of different approaches. Firstly, the standard DEA results will be discussed and the extent to which efficiency differences exist between European and Australian airports will be analysed. A second issue will be to assess the scale efficiency patterns and whether differences appear between the two continents. The third element will be to compare the DEA efficiency results with partial productivity measures in order to assess the correspondence between the two approaches. This is followed by a comparison between DEA and FDH efficiency measures.

4.1 Technical Efficiency

For each airport two types of DEA efficiency measures can be calculated:

- the so-called pooled DEA efficiency score, i.e. the efficiency score obtained when the European and Australian airports are analysed as one sample
- the so-called separate efficiency score where the European and Australian airports are analysed separately

The ratio between the separate efficiency score and the pooled efficiency score can be used to consider the impact of the institutional framework on efficiency variations between European and Australian airports. This ratio is calculated as the pooled efficiency score divided with the separate efficiency score. The ratio should be interpreted as follows. If the pooled efficiency score for a specific airport is equal to the separate efficiency score, it implies that all inefficiency is caused by technical (and scale) inefficiency. However, if the pooled efficiency score is smaller than the separate efficiency score then it means that some of the inefficiency found for that airport with the pooled sample is not present when the efficiency score is calculated with the continent specific sample[4]. In other words, some of the inefficiency cannot be explained as technical inefficiency but is caused by the airport being placed in a less optimal institutional framework for that continent compared to the other continent. The ratio takes values from zero to 1 with 1 implying continent efficiency, and values less than 1 continent inefficiency.

Below, two types of DEA models are examined: (1) a DEA model with constant returns to scale providing efficiency information on pure technical and scale efficiency taken together (DEA-C), (2) a DEA model with variable returns to scale identifying pure technical efficiency only (DEA-V). Using (1) and (2) allow for calculating scale efficiency measures. Looking first to the separate DEA-C efficiency scores the results show that for both European and Australian airports inefficiencies are present. 7 Australian airports (out of 12) are inefficient while 20 European airports (out of 25) are inefficient. The average efficiency score for Australian airports is equal to 0.77 compared to an average of 0.66 for European airports, see Table 2. These results indicate that Australian airports on average achieve higher efficiency scores than is the case for European airports.

Table 2. Average Values for Separate, Pooled and Continent Efficiency Measures, DEA-C

	European Airports		Australian Airports
Separate Efficiency	0.655		0.766
Mann-Whitney Test		0.0951	
Pooled Efficiency	0.562		0.760
Mann-Whitney Test		0.014	
Continent Efficiency	0.864		0.993
Mann-Whitney Test		0.0003	

The Mann-Whitney test examines whether the data support a null-hypothesis that the efficiency scores for European and Australian airports are from the same distribution. This null-hypothesis cannot be rejected at a 5% significance level. The pooled efficiency scores show a similar pattern where the average efficiency score for Australian airports is equal to 0.76 compared to 0.56 for European airports. In this case the Mann-Whitney test implies that the null-hypothesis (the efficiency scores for Australian and European airports are from the

[4] The pooled efficiency score cannot obtain a value greater than the separate efficiency score because a larger sample increases the possibilities for dominance and therefore implies an efficiency score smaller than or equal to the separate efficiency score.

same distribution) is rejected. On average the Australian pooled efficiency scores are significantly higher than the European ones. As this is only partly (and insignificantly) caused by technical efficiency differences, the main reason must be obtained through differences in continent efficiency. The last column shows that average European continent efficiency is 0.86 while Australian continent efficiency is equal to 0.99. This difference is significant according to the Mann-Whitney test (see Table 2). Overall, the institutional framework differences between Australian and European airports seem to account for efficiency differences between the two continents' airports.

Results concerning pure technical efficiency scores only (DEA-V) are shown in Tables 3 and 4. Similar to the DEA-C efficiency scores, the DEA-V efficiency scores for Australian airports are on average higher than the ones calculated for European airports. This conclusion holds for both input and output based DEA-V efficiency measures. The difference to the DEA-C efficiency scores is that as expected the DEA-V scores are higher than the DEA-C scores because the efficiency is calculated assuming the scale of activity to be given.

Table 3. Average Values for Separate, Pooled and Continent Efficiency, DEA-V, Input based

	European Airports		Australian Airports
Separate Efficiency	0.774		0.930
Mann-Whitney Test		0.0256	
Pooled Efficiency	0.663		0.928
Mann-Whitney Test		0.0028	
Continent Efficiency	0.847		0.997
Mann-Whitney Test		0.0011	

For all the input-based efficiency measures the Mann-Whitney tests imply a rejection of the null-hypothesis such that the Australian airports are more efficient than the European airports. In contrast to the DEA-C results, the Mann-Whitney tests show significant differences for all 3 efficiency measures. A significant difference did not appear for the DEA-C separate efficiency scores. This could indicate that European airports have better input scale efficiency than the Australian airports since the DEA-C measure is a combination of technical and scale efficiency. This aspect will be examined in the following section. The Mann-Whitney test results for the output based DEA-V efficiency scores are shown in table 4. These results have a similar pattern compared to the results for the DEA-C efficiency scores. The null-hypothesis that there are no differences between Australian and European efficiency scores, is rejected for the pooled and continent efficiency measures but accepted for the separate efficiency measure. In the next section we will examine what impact this pattern has on output scale efficiency differences between European and Australian airports.

Table 4. Average Values for Separate, Pooled and Continent Efficiency, DEA-V Output based

	European Airports		Australian Airports
Separate Efficiency	0.773		0.857
Mann-Whitney Test		0.1271	
Pooled Efficiency	0.677		0.854
Mann-Whitney Test		0.0307	
Continent Efficiency	0.875		0.997
Mann-Whitney Test		0.0010	

4.2 Scale Efficiency

Table 5 shows the average values for input and output scale efficiency for Australian and European airports. The average scale efficiency level varies between 0.80-0.90 such that among both Australian and European airports scale inefficiency is present. For the pooled sample 3 European and 5 Australian airports are scale efficient measured in terms of inputs and outputs. As expected European airports have on average higher input scale efficiency compared to Australian airports while Australian airports have higher output scale efficiency than the European airports. However, these scale efficiency differences are not statistically significant as the Mann-Whitney test for each of the calculated scale efficiency measures could not reject the null-hypothesis of similar scale efficiency level for Australian and European airports.

Table 5. Average Values for Scale Efficiency Measures

	European Airports		Australian Airports
Input Scale Eficiency (Separate Samples)	0.838		0.813
Mann-Whitney Test		0.390	
Output Scale Efficiency (Separate Samples)	0.843		0.892
Mann-Whitney Test		0.161	
Input Scale Efficiency (Pooled Sample)	0.857		0.810
Mann-Whitney Test		0.488	
Output Scale Efficiency (Pooled Sample)	0.838		0.888
Mann-Whitney Test		0.095	

Normally, a DEA analysis can also indicate the direction of the scale inefficiency, i.e. too high scale (decreasing returns to scale) or too low scale (increasing returns to scale). A possible measure to be used is $\sum_k 8_k$ calculated together with the efficiency score[5]. This measure will be used to indicate the relation between returns to scale and size, where size is measured in so-called Work Load Units (WLU)[6]. In Figure 1 the logarithm to $\sum_k 8_k$ is depicted against WLU, where two measures for $\ln(\sum_k 8_k)$ are included: one measure is based on the separate samples (dark squares) and another one is based on the pooled sample (light squares). The figure shows, as expected, a clear positive relationship between $\ln(\sum_k 8_k)$ and WLU such that the higher the level of WLU the larger is the value of $\sum_k 8_k$. It is possible to indicate the optimal scale from Figure 1 by determining the WLU levels for which $\ln(\sum_k 8_k)$ is equal to zero. The figure suggests that the optimal scale of airport operation varies considerably from small Australian airports like Coolangatta and Canberra with 800000 and 1430000 Work Load Units to Heathrow airport with 58000000 Work Load Units. This pattern is independent of the $\sum_k 8_k$ measure used. Concerning the direction of scale inefficiency the figure suggests that Australian airports are producing with increasing returns to scale while European airports are producing with decreasing returns to scale. Therefore, Australian airports could reach an optimal scale by producing on a larger scale whereas European airports could achieve the optimal scale by reducing the scale of operations. This conclusion should not be overstated because of the non-uniqueness of $\sum_k 8_k$, what has been shown here is merely an indication of scale efficiency patterns.

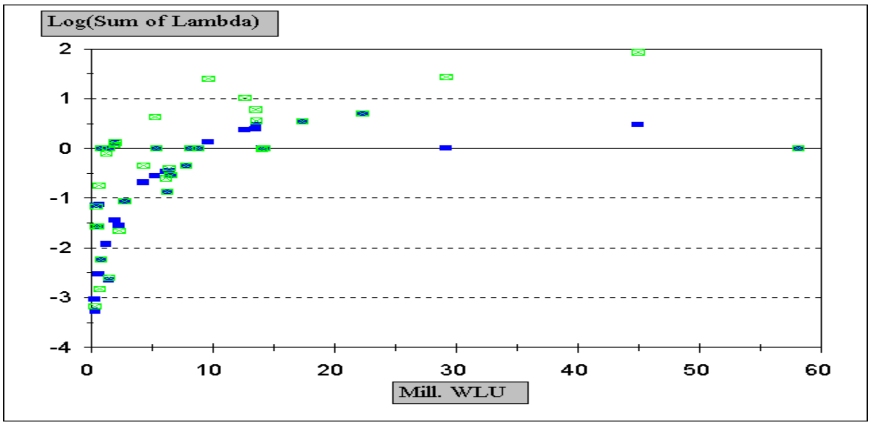

Figure 1. $\ln(\sum_k 8_k)$ depicted against Work Load Units.

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5 In general, there is a clear defined correspondence between returns to scale and $\sum_k 8_k$. Thus: if $\sum_k 8_k=1$ the observation will, normally, have constant returns to scale, if $\sum_k 8_k \leq 1$ then the observation will, normally, produce with increasing returns to scale and if $\sum_k 8_k \geq 1$ then the observation has, normally, decreasing returns to scale. In Banker & Thrall (1992) it was shown that these relationships might not hold in all cases. This is due to the fact that the value of $\sum_k 8_k$ is not uniquely determined. For a given solution several values of $\sum_k 8_k$ might exist. Usually, this problem is, however, of limited influence such that conclusions can be based on $\sum_k 8_k$.

6 Work Load Units are defined as follows: One terminal passenger is equal to one Work Load Unit, but transit passengers are excluded. 100 kilograms of freight/mail constitute one Work Load Unit. Both air freight and air mail are included whereas trucked freight is not.

4.3 DEA versus Partial Productivity Measures

Below, the efficiency scores from DEA are compared to partial productivity measures: (1) terminal passengers per total costs, (2) cargo per total costs, (3) Work Load Units per total costs. These comparisons provide insight into whether the results from DEA are consistent with results from other performance measurement methods. Below, we will analyse the results and discuss the implications. Table 6 shows the Pearson Correlation Coefficient and Spearman Rankorder Correlation Coefficient for each productivity measure with respect to the pooled DEA-C efficiency scores. The Pearson Correlation Coefficient is concerned with the association between the absolute variation for two measures whereas the Spearman Rankorder Correlation Coefficient is concerned with the association between the relative ordering for the two measures, see Siegel & Castellan (1988).

Table 6. Correlation between DEA Efficiency Scores and Partial Productivity Measures

	Pearson Correlation Coefficient	**Spearman Rankorder Correlation Coefficient**
DEA-C vs. Passengers/Costs	0.74	0.71
DEA-C vs. Cargo/Costs	0.74	0.72
DEA-C vs. WLU/Costs	0.68	0.71

All correlation coefficients are positive and significantly different from zero, such that the null hypothesis of no association between DEA-C and the partial productivity measures cannot be accepted. These findings imply that the information from DEA is relatively consistent with information from partial productivity measures. However, as it is not a perfect correlation, it is possible to reach different conclusions about performance for specific airports. Therefore, the appropriate recommendation should be to use DEA along with partial productivity measures to obtain as much information as possible about the observations.

4.4 DEA versus FDH

FDH efficiency scores have been computed for the pooled airport sample in terms of inputs and outputs. Overall, 14 European airports and 11 Australian airports are FDH efficient in terms of inputs or outputs. The average FDH input efficiency score for European airports is 0.87 while the average for Australian airports is equal to 0.99. Similarly, the average FDH output efficiency score for European airports is equal to 0.85 compared to the average for Australian airports equal to 0.99. In correspondence with the DEA results the FDH results thus show that Australian airports have higher efficiency scores than European airports. The calculation of FDH efficiency scores allows an examination of the deviation between DEA and FDH. Table 7 shows the decomposition of the average ratio between DEA-C efficiency scores and FDH input efficiency scores into average input scale efficiency and the average ratio between DEA-V input efficiency scores and FDH input efficiency scores. A similar decomposition is shown in Table 8 for output efficiency scores.

Table 7. Decomposition of the average ratio of DEA-C to FDH input efficiency scores

	DEA-C/FDH	Input Scale Efficiency	DEA-V/FDH	Deviation between DEA-V and FDH
European airports	0.643	0.857	0.754	0.246
Australian airports	0.764	0.810	0.936	0.064

Table 8. Decomposition of the ratio of DEA-C to FDH output efficiency scores

	DEA-C/FDH	Output Scale Efficiency	DEA-V/FDH	Deviation between DEA-V and FDH
European airports	0.659	0.838	0.784	0.216
Australian airports	0.764	0.888	0.858	0.142

Tables 7 and 8 show that the deviation between DEA-V and FDH is larger for European airports than for Australian airports. The difference between Australian and European airports is strongest for the deviation between DEA-V and FDH with respect to input efficiency scores. The information in the tables supports the indication from the DEA analysis that factors not included in the analysis could account for the efficiency differences. Possible factors include institutional/organisational differences.

5. Conclusion

This paper has presented the results of an analysis of efficiency patterns for Australian and European airports using the non-parametric techniques DEA and FDH. Overall, the paper has demonstrated that it is feasible to use these techniques to examine the productive performance of airports. In particular, the application has shown that DEA and FDH can provide useful information regarding airport efficiency patterns. A major conclusion of the analysis is that given the specification of inputs and outputs, Australian airports appeared to achieve higher levels of efficiency than the European airports. This aspect was examined by undertaking the efficiency analysis in two ways: (a) calculation of efficiency using the pooled sample such that European and Australian airports form the best-practice frontier together, (b) calculation of efficiency using separate samples such that two best-practice frontiers are derived (one for European airports and one for Australian airports). From this examination it appeared for both DEA-C and DEA-V that the efficiency scores for European airports were significantly lowered by using the pooled sample rather than the separate sample, this pattern was not obtained for Australian airports. This pattern suggests that a “continent” impact is present accounting for the efficiency differences rather than merely being related to technical efficiency differences. Possible explanations for this continent impact are likely to relate to institutional differences including the regulatory and planning frameworks for airports. The efficiency results obtained using DEA corresponded well to the ones obtained from partial productivity measures. However, the correspondence was not perfect indicating that the use of DEA along with partial productivity measures could be appropriate to obtain as much information about the observations as possible.

Further research will analyse the causes for the detected efficiency differences between European and Australian airports. This will include detailed examination of the legal, organisational and planning frameworks established in the different European countries and Australia in order to determine how these frameworks influence airport performance.

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