

ABSTRACT

Title: ASSESSMENT OF PRODUCTIVE
EFFICIENCY OF AIRPORTS

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Doctoral of Philosophy, 2006

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The move towards commercialization and privatization has pressured airports to become more productive and competitive. The need to devise an overall (total) productivity measure is increasingly important in airport business. The dissertation made three major research contributions. First, it assessed the productivity of airports operating in multiple airport systems (MASs). Second, it developed a more complete total factor productivity measure by considering joint production of desirable and undesirable outputs. Third, it developed models for explaining variations in productive efficiency. These are accomplished in two case studies.

In case study 1, the Data Envelopment Analysis (DEA) is used to assess relative total productivity of 72 airports operating in 25 MASs during 2000 – 2002. The results indicate that highly utilized airports such as O'Hare International, Los Angeles International, Heathrow/London and LaGuardia are classified as efficient. The Censored Tobit regression model suggests that runway utilization market dominance, proportion of international passengers and ownership can be used to explain variations in productive efficiency.

In case study 2, the directional output distance function is applied to assess the productivity of 56 U.S. commercial airports during 2000 – 2003. Delays are considered as undesirable outputs. There are several important findings and insightful implications. First, about half of U.S. airports are actually operated efficiently. These airports include busy airports such as Hartsfield-Jackson Atlanta, LaGuardia, and Memphis together with less busy airports with relatively low delays such as Baltimore/Washington International and Oakland International. Second, the overall system has potential to accommodate about 1,550 million passengers, 26 million movements and 34 million tons of cargo. Third, during 2000 - 2003, annual growth of productivity is modest in the range of -1.3% to +1.8%. Fourth, by ignoring delays the assessment provides drastically different results in terms of number of efficient airports, level of inefficiency, ranking, and estimated maximum possible outputs. Fifth, the consideration of undesirable output is as important as the consideration of additional inputs and desirable outputs. The Censored Tobit regression model suggests that runway utilization, proportion of international passengers and average delay per passenger can be used to explain variations in productive efficiency.

ASSESSMENT OF PRODUCTIVE EFFICIENCY OF AIRPORTS

By

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park in partial fulfillment
of the requirements for the degree of
Doctoral of Philosophy
2006

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Preface

As a transportation professional, I am rather fortunate to be able to work in all modes of transportation, i.e., land, water and air. This dissertation adds another chapter in air transportation experience to my career. I was interested in aviation since I was an undergraduate student studying pavement design for airfield. But it was not until 1990s that I realized the fascination of aviation systems planning when I worked as a transport engineer in two projects, i.e., 1) Airport Systems Master Plan Study in Thailand and 2) Feasibility Study and Master Plan Development for Joint Military-Civilian Used U-Taphao International Airport. It was so memorable time to work with several aviation professionals including an old-hand project manager and a good friend of my family, Mr. Clifford R. King (then with Louis Berger International, Inc., currently a senior project manager at Bechtel Corporation). Since then, I have had aviation in my heart.

This dissertation was accidentally started while I was completing a term paper on airport choice modeling in Baltimore-Washington multiple airport system for a class ENCE688Y (Advances in Transportation Demand Analysis) in the Fall 2002 taught by Professor Hani Mahmassani. The literature review led me to learn further that aviation community is interested in measuring performance of airport for a variety of reasons, including benchmarking and investment appraisal. I was so surprised to know that research to assess overall airport performance had just started in late 1990s. I then started working on the topic seriously and published our first paper “Benchmarking efficiency of airports in the competitive multiple-airport systems: the international perspective” at the 19th Annual Transport Chicago Conference in June 2004 (with Professor Ali Haghani). Subsequently, Professors Paul Schonfeld, Martin Dresner and Robert Windle kindly

accepted the invitation to jointly work and improve the quality of papers. We co-authored another two papers for the 84th and 85th Transportation Research Board Annual Meeting, Washington DC, 2005 - 2006.

I am particularly grateful to many valuable comments from my co-authors and several anonymous reviewers. Their comments enabled us to extend and expand the scope of our research, essentially to answer practical aviation issues. One of the frequent comments is about my overemphasis on quantity of outputs and ignoring their quality, although measures such as delays are a major concern of the airport management. Such comments bring the dissertation to the last phase, i.e., the assessment of airport productivity with joint consideration of desirable and undesirable outputs. I stumbled upon a relatively new theory in production economics, i.e., the directional output distance function, while I was searching for a method to deal with undesirable outputs in the productivity assessment.

I received useful guidance from Professors Rolf Färe and Shawna Grosskopf of Oregon State University who devised the theory and eminently populated applications in recent years. We could start a new research on airport productivity by jointly considering delays as major output measures, though undesirable, along with other traditional desirable outputs (e.g., number of passengers, aircraft movement, and freight throughput). We have published the new findings in three papers so far, i.e., National Urban Freight Conference, Long Beach, CA (February 2006), the 47th Annual Transportation Research Forum, New York (March 2006) and the 10th Annual Air Transport Research Society (ATRS) World Conference, Nagoya, Japan (May 2006). This dissertation is partly based

on the above-mentioned six publications and another paper which is under review by Transportation Research Part E: Logistics and Transportation Review.

Dedication

To my mother, U-SA Kow whose vision is always clear and correct. You enabled so many things in my life and enlighten me in many ways. I can be successful today because I have you, mom. I really can't thank you enough.

Acknowledgements

Always for this level of accomplishment, there are many people directly or indirectly involved. I apologize if I unintentionally omit one of you. First of all, I wish to express my gratitude to my academic advisor, Professor Ali Haghani for continuous support throughout my doctoral study. Working under his supervision has been particularly rewarding and most gratifying, especially since I have been able to carry out research in various fields (e.g., logistics, travel behavior and demand modeling, GIS, operations research, and aviation system planning) with his full support and confidence.

I also want to thank Professors Kelly Clifton, Martin Dresner, Hani Mahmassani, Paul Schonfeld, and Robert Windle for serving in my dissertation committee. Their comments and suggestions were of particularly great value to the quality of the dissertation. In particular, I highly appreciate friendly advice from Professors Paul Schonfeld, Robert Windle and Martin Dresner while we were co-authoring several papers. I learned endless lessons from them and really enjoyed working with them. Hopefully, we could continue the productive collaboration in the future endeavors.

Special thanks also go to Professors Rolf Färe and Shawna Grosskopf of Oregon State University for their guidance on the theory and rich applications of the directional output distance function. I greatly benefited from a string of communications with them. In addition, comments and discussion with Professors Steven Burks of the University of Minnesota and B. Starr McMullen of the Oregon State University greatly improve the quality of the dissertation. There are also many airport staff members and managers in the U.S. and around the world who willingly shared their airport information and had fruitful discussions about airport business. I highly appreciate their contribution.

Finally, I want to share my success and pleasure with my wonderful family members who have stood beside me with love and encouragement for years. I am forever indebted to their immeasurable, constant and continuous and tireless support during my study, especially, my wife, Laddawan whose sacrifice has made nothing impossible. I am so proud to have you and our lovely three children, Nawanont, Nonthida and Phuwanont in my life. I also want to express the gratitude to my wife's family members who always strongly encourage and support us. It is the highest honor of my life to have such a great family support.

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CHAPTER 1

INTRODUCTION

1.1 Airport business

The aviation industry has experienced swift ups and downs after the deregulation of air transportation in the late 1970s. The competition in the air transportation industry is now fierce. In recent years, it has become more common for airports to advertise and promote their services to lure customers just like other businesses do. Airport business models have changed dramatically from being perceived as a fundamental public service in the same way as roads and public transport, to a commercial activity. Over the past twenty years, it has become obvious that airports can actually be run as highly successful and profitable businesses (Doganis, 1992).

On one hand, airports are an essential part of the air transportation system. They provide all the infrastructure needed to enable passengers and freight to transfer from surface to air mode of transport and to allow airlines to take off and land. On the other hand, airports also offer a wide variety of commercial facilities ranging from shops, restaurants, hotels, and conference services (Graham, 2003; Jarach, 2005). There is no doubt that an airport can be a big business. The public floatation of the British Airports Authority in the summer of 1987 is valued at £1.3 billion (Doganis, 1992). It is expected that rapid growth of air traffic would require enormous amount of funding to support airport improvement programs. This places increasing pressures on public finance. Such pressures have led governments all over the world to consider privatization and commercialization to relieve them from the financial burden of airport ownership

(Ashford, 1999; Francis and Humphreys, 2001). Airport managers have to adapt themselves in response to such pressures as well. They are now acting more like corporate business managers. They think strategically, identify markets, set objectives and goals, cast competitive strategies, implement, monitor, evaluate outcomes, and respond to the dynamics of market competition. Their job is much more complicated than before.

1.2 Importance of airport productivity study

To study airport productivity is to study the relationship between inputs and outputs of airport operation. With such a relation, airport managers can easily determine the probable traffic level that airports should accommodate, given any level of inputs. This is very useful in monitoring, managing and planning airports. In addition, it allows managers to benchmark their operational performance with peers and set appropriate output targets for improving their business.

Until the 1980s, the systematic monitoring and comparing of airport performance was not a widely practiced activity within the airport industry. This can largely be attributed to insufficient commercial and business pressures for airports and the general lack of experience of benchmarking techniques within the public sector. With airport privatization and commercialization has come a marked interest in performance comparisons and benchmarking. As airports become more commercially-oriented, they have been keen to identify the strong performers in the industry and adopt what are seen as best practices (Graham, 2003). Hooper and Hensher (1997) commend that the growing importance of airport performance measurement is accompanied by the trend toward corporatized or even privatized airports. In recent survey from the world's top 200 busiest

passenger airports (Francis, Humphreys and Fry, 2002; Humphreys and Francis, 2002), the results reveal that airport managers are now using several performance measures to monitor their businesses.

Several authors comment on the importance of studying airport productivity. For instance Sarkis (2002) argues that evaluating airport operational efficiency is important for a number of reasons including communities' reliance on airports for economic well-being; air carriers' ability to choose among competing airports due to deregulation, and the fact that federal funding for airport improvements is based on performance measures. Performance evaluation and improvement studies of airport operations have important implications for a number of airport stakeholders. They assist air carriers in identifying and selecting more efficient airports on which to base their operations. Likewise municipalities would benefit from efficient airports in terms of attracting business and passengers. They also assist federal government in making effective decisions on optimal allocation of resources to airport improvement programs, and in evaluating the efficacy of such programs on the bottom line efficiency of airports. Finally, benchmarking their own airports against comparable airports is one way for operations managers to ensure competitiveness (Sarkis and Talluri, 2004).

The need to develop appropriate service and productivity indicators for airport operation has been recognized and there is a small, but growing literature on the subject. Though there have been appeals to measure "overall productivity", there is little evidence that the tools of productivity measurement that have been applied in other parts of the transport sector have had serious application in the case of airports (Tretheway, 1995). As the literature review in Chapter 2 will reveal, it only began in the late 1990s. Until

recently, a good number of studies have been conducted comparing productivity and operational efficiency of airports around the world, including Australia (Abbott and Wu, 2001; Hooper and Hensher, 1997), U.K. (Parker, 1999), U.S. (Gillen and Lall, 1997, 1998; Bazargan and Vasigh, 2003; Sarkis, 2000; Sarkis and Talluri, 2004), Spain (Martin and Roman, 2001), Brazil (Fernandes and Pacheco, 2001, 2002, 2005; Pacheco and Fernandes, 2003), Japan (Yoshida, 2004; Yoshida and Fujimoto, 2004). Occasionally the scope was expanded beyond a country to one continent such as Europe (Pels, Nijkamp and Rietveld., 2001, 2003) and international level (Adler and Berechman, 2001; Oum and Yu, 2004; Oum, Yu and Fu, 2003). Surprisingly, none has ever studied the productivity of airports operating in a specific market such as multiple airport systems (MAS), although they involve much more capital investment. At best, MAS airports are treated in the mixed samples with airports from single airport systems. The exception are only Pathomsiri and Haghani (2004); Pathomsiri, Haghani and Schonfeld (2005); Pathomsiri, Haghani, Dresner and Windle, (2006a) which will be summarized within this dissertation.

Moreover, airport productivity research is rather restricted in the sense that productive efficiency is solely based on consideration of marketed outputs. Non-marketed outputs or so-called “undesirable outputs” such as delays have been largely ignored, though they are also a major concern to airport stakeholders. This may be due to the lack of analysis technique. In principle where there is joint production of desirable and undesirable outputs, accounting for both of them intuitively should provide a more complete measure of airport productivity.

1.3 Motivation of the dissertation research

This dissertation is motivated by several factors. First, it is clear that the aviation society still has insufficient understanding regarding the productivity of airports operating in specific markets such as multiple airport systems. Second, the aviation society lacks understanding of the relationship between airport's inputs and outputs, especially when undesirable byproducts are taken into consideration. Development of an applicable model is eminently necessary. The results should give a more complete measurement of airport productivity. Third, it is believed that the results have substantial implications which are very useful for managing airports. Last but not least, as the literature review in chapter 2 will reveal, the dissertation is a pioneering work. It likely creates an impact and entices researchers to re-think the way they assess productivity of airports. It is expected that further development of the applicable models for fairer assessment will follow.

1.4 Research objectives and scope

This dissertation attempts to address the shortcomings of the previous airport productivity studies. In particular, it aims to accomplish the following four main objectives.

- 1) Assess the productivity of airports operating specifically in multiple airport systems as well as develop a model for predicting their relative efficiency.

- 2) Assess the productivity of U.S. commercial airports by accounting for joint production of desirable and undesirable outputs as well as develop a model for predicting their relative efficiency.

3) Estimate changes of airport productivity and sources of productivity growth during the study period, i.e., 2000 - 2003.

4) Analyze the impact of the inclusion of undesirable outputs on the productivity measurement and productivity growth.

Since the research aims to provide timely information useful for managing airport in the modern era, the study period will span over recent years, i.e., 2000 – 2002 for research objective 1) and 2000 – 2003 for research objectives 2) to 4). Most data are expected to be from consolidated databases such as Federal Aviation Administration (FAA), Airports Council International (ACI), and Air Transport Research Society (ATRS). Supplement data may be collected directly from primary sources.

1.5 Research contributions

The dissertation makes three major research contributions. First, rather than using mixed sample of airports, it assesses the productivity of airports operating in a similar market structure, i.e., multiple airport systems (MASs). Second, unlike previous airport productivity studies, this dissertation makes the first attempt to develop a more complete total factor productivity measure by also taking into account undesirable byproducts from airport operations, i.e., delays. Third, this dissertation also develops causal models for explaining variations in productive efficiency. The three contributions are accomplished by using recent panel data in two case studies.

1.6 Organization of the dissertation

The dissertation is organized into eight chapters. The first chapter discusses the revolution of airport business, importance of airport productivity study, motivation of the

dissertation research as well as objectives and scope of the research. Chapter 2 reviews literature related to productivity study with emphasis in airport sector. Classification of productivity measures and a methodology to compute them are described. Since Data Envelopment Analysis is the most widely-used method for measuring airport productivity, its concept is briefly explained in this chapter to provide basic understanding of model development and its weaknesses. The DEA model will be used in one of the two case studies in this dissertation.

Chapter 3 explains in details the proposed research methodology for assessing productivity of airports where joint production of desirable and undesirable outputs is taken into account. This chapter starts with the characterization of production possibility set, and illustration of output distance function and its modification, i.e., the directional output distance function which is the adopted model for analysis in the case study. The chapter also illustrates the computation of Malmquist and Luenberger productivity indexes and their components that are useful for explaining changes of productivity over time.

Chapter 4 describes the first case study. The study is to assess productive efficiency of airports operating in MASs by using DEA as well as develop causal models for explaining variations in efficiency level. Chapter 5 presents and discusses the results from case study 1. Chapter 6 describes the second case study of 56 U.S. commercial airports. The contents cover modeling of airport operation, selection of inputs and output measures and characteristics of samples. The directional output distance function is applied to access the productivity of these airports. Chapter 7 presents and discusses the results. It provides contrast comparisons between with and without consideration of

undesirable outputs (delays). Other substantial results include productivity growth during 2000 – 2003, statistical analysis and scenario analysis. Important findings and insightful information are pointed out. Lastly, chapter 8 concludes the dissertation and suggests some potential areas for future research.

CHAPTER 2

LITERATURE REVIEW

This chapter rigorously reviews previous work directly related to airport productivity. The focus is on the classification of productivity measurement, the applied methodologies for measuring productivity, discussion of their advantageous and disadvantageous as well as the consideration for use. Summary of major findings and implications are also discussed.

2.1 Productivity measures

In economics, productivity is defined as the amount of output per unit of input. In other words, the productivity measure is the ratio between output(s) and input(s). The definition, though very concise, is quite problematic to be applied in assessing productivity of airports. This is essentially due to the nature of airport operation which takes multiple inputs (such as labor and capital) for producing multiple outputs (such as movement of aircrafts, number of passengers and cargo throughput). Given various possible inputs and outputs, there are really many different ways of computing the productivity measure. Nevertheless, productivity measures can be categorized broadly into two groups of either partial factor or total (overall) factor productivity measures.

2.1.1 Partial Factor Productivity (PFP) measure

Partial factor productivity (PFP) measures generally relate an airport's output to a single input (factor). Labor productivity measures such as passengers per employee, aircraft movements per employee and ton landed per employee, are good examples. Table

2.1 summarizes more examples of PFP measures that have been used in airport business. A recent survey (Humphreys and Francis, 2002) revealed that the move towards privatization and commercialization has led to new performance measures being introduced to reflect the changing management goals. New measures fall into three categories, i.e., 1) financial measures to monitor commercial performance, 2) measures to meet the requirements of government regulators and 3) environmental measures.

PFP measures have the advantage of being easy to compute, requiring only limited data and are easy to understand. As a result, many airport managers around the world usually adopt PFP measures to benchmark their performance (Francis, Humphreys and Fry, 2002; Humphreys and Francis, 2002). It is common to see such measures appear routinely in aviation trade publications (ACI 2002-2004; ATRS 2002 – 2003).

Nevertheless, the measures can often be misleading when looking at the overall picture of the airport operation. For instance, it is possible to raise productivity in terms of one input, at the expense of reducing the productivity of other inputs. In the case of airports, which are fairly capital intensive, a partial productivity measure of labor productivity does not give a very clear picture of whether the performance of the institution is being improved (Abbott and Wu, 2002). Moreover, there are many possible PFP ratios, given multiple inputs and outputs of airport operation. There is usually a tradeoff among those measures. Airport may look better on one measure but can be worse on the others. As far as the overall assessment is concerned, it is preferable to use some form of overall (total) productivity measures that better shows the relation between all outputs and inputs.

Table 2.1 Examples of partial factor productivity measures in aviation sector

Scope of measure	Category	Examples of performance measures
Global performance of airport	Profitability	income per passenger
		rate of return on capital
		revenue to expenditure ratio
		profit per workload unit (WLU)
	Cost-efficiency	cost per WLU (excluding depreciation and interest)
		operating cost per WLU
		capital cost per WLU
		labor cost per WLU
		aeronautical cost per WLU
	Cost-effectiveness (revenue earning)	total revenue per WLU
		aeronautical revenue as a share of total
		aeronautical revenue per WLU
		non-aeronautical revenue per WLU
concession revenue per area		
Partial productivity measures	Capital productivity	value added per unit of capital costs
		WLU per unit of net asset value
		total revenue per unit of net asset value
	Labor productivity	WLU per employee
		revenue per employee
		value added per employee
		passengers/employee
Performance of particular processes	Runways	aircraft movements per runway
		aircraft movements per length of runway
		aircraft movements per hourly capacity
		passenger per aircraft movement
	Passenger processing	service time for check-in
		time to reclaim baggage
		gate utilization rates
		passengers per terminal area
	Baggage handling	baggage handled per unit of time
		baggage service reliability over time
Customer service	Passengers	distances to reach departure gates
		crowding (passenger density)
		variability in service times
		passenger service ratings
	Cargo	average time required to deliver freight at cargo terminal prior to aircraft departure
		theft and breakage rates
	Airlines	index of aeronautical charges
		index of non-aeronautical charges
		aircraft turn-around times

Note: A “workload unit (WLU)” is equal to one passenger or 100 kilogram of cargo.

Source: Hooper and Hensher (1997); Francis, Humphreys and Fry (2002); Humphreys and Francis (2002); Oum, Yu and Fu (2004).

2.1.2 Total Factor Productivity (TFP) measure

In early 1990s, the literature on performance measurement for airports was focused on the use of partial measures that yield an incomplete representation of the important relationship between multiple inputs and outputs. The lack of published research on overall measures of performance places a limit on our understanding of productive processes in the airport sector (Hooper and Hensher, 1997). As partial factor productivity measure indicates, performance has many dimensions. The growing literature on measuring the performance of airports is addressing the limitations of PFP measures in capturing all of those dimensions.

A common way to deal with the problem of too many PFP measures is to derive an aggregate measure that takes into account all significant inputs and outputs simultaneously. Such measure is often called “Total Factor Productivity (TFP)” measure. Such overall TFP measure is useful for managers who are assessing the global productivity of an airport. It considers that different airports face different economic conditions and therefore may use input factors in varying proportions. For example, an airport that exhibits low labor productivity may not necessarily be inefficient from an overall perspective; it may merely be substituting capital with labor to take advantage of a wage rate (Nyshadham and Rao, 2000). TFP based measures have recently received increased attention in air transportation research and become a preferred measure. See for example Gillen and Lall (1997, 1998); Hooper and Hensher (1997); Oum and Yu (2004); Pathomsiri, Haghani, Dresner and Windle (2006a); Pels, Nijkamp and Rietveld (2001, 2003); Windle and Dresner (1992); and Yoshida and Fujimoto (2004). Since the TFP

measure is more suitable than PFP measures for assessing the productivity of airports, the subsequent review will focus on the methodology to derive the TFP measure.

2.2 Methodology for computing TFP measure

There are several methods for deriving the TFP measure. The methods generally fall into two broad categories i.e., parametric and non-parametric approaches. Each approach has advantages and disadvantages. Their applicability usually depends on the availability of data. In some cases, both approaches are used to obtain complementary results (Pels, Nijkamp and Rietveld, 2001, 2003) or confirm the conclusions (Yoshida and Fujimoto, 2004).

2.2.1 Parametric approach

Conceptually speaking, the parametric approach works in three major steps, i.e.,

- 1) Transforming inputs into a common unit by assigning appropriate weights to individual inputs
- 2) Transforming outputs into a common unit by assigning appropriate weights to individual outputs so that an aggregate output can be computed and
- 3) Given *a priori* production function which represents logical relationship between the composite output in 2) and various transformed inputs in 1), estimate a set of parameters associated with individual transformed inputs.

The results will give an estimated production function of airport operation explaining the transformation of inputs into outputs. With this function, it is possible to estimate the probable output level for a given set of inputs. Whenever the actual output is below the probable level, an airport is not being operated efficiently. In addition, by

assuming that airports in the sample are similar; the productivity of airports can be benchmarked by comparing the difference between the actual output and the probable level. The further from the probable level means the less efficient operation. There are two major issues involved when one decides to use the parametric approach. First, what are the appropriate weights for transforming inputs and outputs? Second, what is the suitable functional form?

Regarding the first question, Hooper and Hensher (1997) argue that the appropriate input weights should be the cost shares which represent the contributions of each input to costs. They also suggested that the output weights be the cost elasticities as long as they are readily available from prior research. However, in the most of empirical studies the absence of such elasticities has led to the use of revenue shares as proxies. Nyshadham and Rao (2000) have also adopted cost and revenue share respectively as input and output weights for their productivity assessment of 25 European airports. Hooper and Hensher (1997) commented that the use of prices as output proxies implicitly presumes that the airport is pricing efficiently but, since monopoly pricing is an issue of concern, it is problematic to derive an output measure from income. Indeed better measures for output quantity would have been landings for aeronautical output and passenger plus meeter-greeter throughput and the volume of cargo handled for non-aeronautical output.

As for the second issue, the choice of *a priori* production function is rather subjective; and its suitability is usually based on the goodness-of-fit. Martin-Cejas (2002) estimates a deterministic cost frontier using translog function to assess the productive efficiency of 31 Spanish airports during 1996 – 1997. Pels, Nijkamp and Rietveld (2001)

estimate two stochastic production frontiers in their productivity study of 34 European airports during 1995 – 1997. The first function has number of passengers as the dependent (output) variable. The second function aims to explain the number of aircraft movements. Both of them are translog function. Based on the same dataset, their subsequent publication (Pels, Nijkamp and Rietveld, 2003) also estimate two stochastic production frontiers with the same two dependent (output) variables, but with different set of explanatory variables. The literature review indicates that translog is the most widely -used function in airport productivity studies.

Although there are issues on weights and selection of production form, the parametric does have some advantages over the non-parametric approach. First of all, it can both measure and explain inefficiency simultaneously. Second, the parametric method allows for statistical testing of the presence of a deviation from the efficient frontier and returns to scale. Table 2.2 summarizes previous studies that used a parametric approach. It can be seen that there are very few studies. Availability of cost and revenue sharing data seem to be a big hurdle that limits the applicability of this approach. Many researchers therefore have resorted to an alternative approach, i.e., non-parametric.

Table 2.2 List of publications on airport productivity studies by parametric approach

Author(s)	Sample	Productivity model	Functional form	Remark
Pels, Nijkamp and Rietveld (2001)	Year: 1995-1997 (pooled cross-section time series) Size: 34 European airports	Stochastic production frontier (SPF)	translog Air transport movements (ATM) = f{constant, number of runways, number of aircraft parking positions at the terminal, number of remote aircraft parking positions} Number of passengers (PAX) = f{constant, number of baggage claim units, number of aircraft parking positions at the terminal, number of remote aircraft parking positions}	- Compute the most productive scale size (mpss) which represents the maximum productivity for any given input-output combination (Banker, 1984).
Martin-Cejas (2002)	Year: 1996 – 1997 (pooled cross-section time series) Size: 31 Spanish airports	Deterministic cost frontier	translog Total cost (TC) = f{unit of traffic transported, labor price, capital price}	- Unit of traffic transported (UT) = number of passengers + (kilograms of freight/100)
Pels, Nijkamp and Rietveld (2003)	Year: 1995-1997 (pooled cross-section time series) Size: 34 European airports	Stochastic production frontier (SPF) and inefficiency model	translog Air transport movements (ATM) = f{constant, year dummy, airport area, number of runways, number of aircraft parking positions at the terminal, number of remote aircraft parking positions} ATM Inefficiency = f{slot coordination dummy, time restriction dummy} Air passenger movements (APM) = f{constant, , year dummy, predicted ATM, number of check-in desks, number of baggage claim units } APM Inefficiency = f{ constant, time restriction dummy, average airlines' load factor}	- All variables (except dummies) are standardized around mean. - Treat number of runways as a fixed factor - Estimate also the DEA model (see Table 2.4 for the same authors)

2.2.2 Non-parametric approach

The key characteristic of non-parametric approach is that it does not need to specify *a priori* production function. No parameter needs to be estimated. Among other methods, index number and Data Envelopment Analysis (DEA) are the most popular in previous airport productivity studies.

The index number method works similarly to the first two steps of parametric approach. Each input (output) needs to be assigned an appropriate weight so that individual inputs (outputs) are transformed into the same unit of measurement. Thus a weighted aggregate input (output) can be computed. The resulting aggregate input/output are called input/output indexes. By definition the total productivity index is the ratio of the weighted aggregate output index to a weighted aggregate input index. The higher value of TFP indicates higher efficiency. Thus the TFP measure can be used to rank performance of airports. Since the method involves weights, the discussion of weight issue in parametric approach is applicable here.

In their productivity study of four Australian airports during 1989 – 1992, Hooper and Hensher (1997) use cost and revenue shares respectively as associated weights to inputs and outputs and obtain aggregate input and output indexes. Similarly, Nyshadham and Rao (2000) also use cost and revenue shares in their productivity study of 25 European airports. Other studies that adopted index number approach to compute TFP measure include Oum, Yu and Fu (2003), Oum and Yu 2004Yoshida (2004), Yoshida (2004), as well as Yoshida and Fujimoto (2004). Table 2.3 summarizes publications on airport productivity studies using index number method.

Table 2.3 List of publications on airport productivity studies using index number method

Author(s)	Sample Year	Model	Input	Output	Remark
Hooper and Hensher (1997)	Year: 1988- 9, 1991-2 Size: 6 Australian airports	Multilateral translog index number of TFP	1. capital stock 2. labor expenditures 3. other costs	1. deflated aeronautical revenues 2. deflated non-aeronautical revenues	- Use share of revenues as weights to compute output index - Estimate two regression models for estimating output-adjusted TFP. One model regressed TFP with output index (composite of cargo tonnages, movements, passengers, employers and labor costs). The other adds airport dummy variable.
Nyshadham and Rao (2000)	Year: 1995 Size: 25 European airports	Multilateral translog index number of TFP	1. operating cost per work load unit 2. capital cost per work load unit 3. other costs per work load unit	1. aeronautical revenue per work load unit (WLU) 2. non-aeronautical revenue per work load unit (WLU)	- A work load unit is defined as either one passenger or 100 kilograms of cargo. - Use percentage share of the revenue as weights to compute output index - Use percentage share of cost as weights to compute input index - Compute Spearman rank correlation between TFP and several PFP measures; then estimate a regression model for explaining TFP by PFP measures.

Table 2.3 List of publications on airport productivity studies using index number method (Continued)

Author(s)	Sample Year	Model	Input	Output	Remark
Oum, Yu and Fu (2003)	Year: 1999 Size: 50 major airports in Asia-Pacific, Europe and North America	Endogenous Weighted (EW) TFP input and output index numbers	1. number of full-time equivalent employees who work directly for an airport operator 2. number of runways 3. number of gates 4. other costs l	1. aircraft movements 2. number of passengers 3. cargo throughput 4. non-aeronautical revenues	- Estimate a regression model for explaining the variation in TFP: $TFP = f\{\text{constant, Asia-pacific dummy, airport size, \% international passengers, \% of aeronautical revenues}\}$
Yoshida (2004)	Year: 2000 Size: 30 Japanese airports	Endogenous weighted (EW) TFP input and output index numbers	1. runway length 2. terminal area	1. aircraft movements 2. number of passengers 3. cargo throughput	
Yoshida and Fujimoto (2004)	Year: 2000 Size: 67 Japanese airports	DEA-Input-CRS DEA-Input-VRS Endogenous weighted (EW) TFP index number	1. runway length 2. terminal area 3. number of employees in the terminal 4. average access cost	1. aircraft movements 2. number of passengers 3. cargo throughputs	- Use DEA efficiency score as truncated dependent variable and estimate a Tobit regression model to check inefficiency of regional airports and airports operated in 1990s. - Use EW-TFP index number as a dependent variable and estimate a regression model to check inefficiency of regional airports and airports operated in 1990s.

Table 2.3 List of publications on airport productivity studies using index number method (Continued)

Author(s)	Sample Year	Model	Input	Output	Remark
Oum and Yu (2004)	Year: 2000 – 2001 Size: 76 airports in Asia Pacific, Europe and North America	Variable Factor Productivity (VFP – input index number)	1. number of full-time equivalent employees who works directly for an airport operator 2. other costs	1. aircraft movements 2. number of passengers 3. cargo throughput 4. non-aeronautical revenues	- Estimate a regression model for explaining the variation in VFP: $VFP = f\{\text{constant, airport size, \% international passengers, \% cargo traffic, capacity constraints, \% of non-aeronautical revenues, outsourcing dummy}\}$

One of the difficulties in using this method is that it requires a complete set of prices and quantity data. In many cases, these data are not available. Due to data limitations Hooper and Hensher (1997) were restricted to a few years during the early 1990s for four airports, so the study essentially presented a very limited indication of the performance of the Australian airport systems. Another weakness in this approach is the use of total revenue of the airports as an indicator of output. It is justifiable as long as prices, and therefore revenue, are not a reflection of the degree of market power of the institution considered. In the case of airports this might be the case and so it is preferable to use a total factor productivity valuation approach that does not depend upon prices that might be distorted by market imperfections (Abbott and Wu, 2002). Martin and Roman (2001) argued that some financial measures can be misleading indicators, as a consequence of the relative market power that might exist. Monopolistic airports might be able to make substantial profits even if they were inefficient. More importantly, prices are applicable for marketed outputs only, but it is difficult to calculate for non-marketed outputs, such as delays, noise and other externalities. During the past decade, aviation researchers have resorted to use an alternative non-parametric method which gets away from weight issue i.e., Data Envelopment Analysis (DEA).

DEA is perhaps the most widely used method for assessing productivity of airport, regardless of approaches. DEA may be a true non-parametric method. It does not require any weights. It does not need to assume a production function. Instead, it builds an empirical piecewise linear production function from sample data. The only required data are the quantity of inputs and outputs. This is perfectly applicable in airport context where the breakdown between revenue and average prices for freight cargo and passenger

traffic are not made available, but output and input volume figures are. Therefore, DEA is the ideal method for estimating TFP measure. During the past decade, DEA seems to be the prevailing method used in assessing airport productivity. Table 2.4 lists publications that adopted DEA as an analytical method. Since DEA is the prevailing method in airport productivity study, the next section will be devoted to the review of DEA. It should be noted that the review is by no means exhaustive, but is focused on model development and some important features. The publications in Table 2.4 will also be referred to more. For more theoretical insights and applications about DEA, a good number of textbooks can be consulted. See for examples in Charnes, Cooper, Lewin and Seiford (1994); Cooper, Seiford and Tone (2000); Zhu (2003); Cooper, Seiford and Zhu (2004); Ray (2004); Cook and Zhu (2005).

Table 2.4 List of publications on airport productivity studies using DEA

Author(s)	Sample Year	Model	Input	Output	Remark
Gillen and Lall (1997)	Year: 1989 – 1993 Size: 23 of the top U.S. airports	DEA- Output-CRS	I. Terminal services 1. number of runways 2. number of gates 3. terminal area 4. number of employees 5. number of baggage collection belts 6. number of public parking spaces	I. Terminal services 1. number of passengers 2. pounds of cargo	- Estimate two Tobit regression models for explaining terminal and movements efficiency
		DEA- Output-VRS	II. Movements 1. airport area 2. number of runways 3. runway area 4. number of employees	II. Movements 1. air carrier movements 2. commuter movements	

Table 2.4 List of publications on airport productivity studies using DEA (Continued)

Author(s)	Sample Year	Model	Input	Output	Remark
Gillen and Lall (1998)	Year: 1989 – 1993 Size: 22 of the top U.S. airports	DEA- Output-CRS	I. Terminal services 1. number of runways 2. number of gates 3. terminal area 4. number of employees 5. number of baggage collection belts 6. number of public parking spaces	I. Terminal services 1. number of passengers 2. pounds of cargo	- Compute Malmquist TFP by component
		DEA- Output-VRS	II. Movements 1. airport area 2. number of runways 3. runway area 4. number of employees	II. Movements 1. air carrier movements 2. commuter movements	

Table 2.4 List of publications on airport productivity studies using DEA (Continued)

Author(s)	Sample Year	Model	Input	Output	Remark
Murillo-Melchor (1999)	Year: 1992 – 1994 Size: 33 Spanish civil airports under management of AENA (Spanish Airports and Air Transport)	DEA-Input-CRS DEA-Input-VRS	1. number of workers 2. accumulated capital stock approximated by the amortization estimated in constant value 3. intermediate expenses	1. number of passengers	- Compute Malmquist index for individual pair of years
Parker (1999)	Year: financial years (as of March 31) from 1988/89 – 1996/97 Size: 22 UK airports, including all of British Airports Authority (BAA)'s major airports	DEA-Input-VRS	1. employment 2. capital stock 3. non labor cost 4. capital cost 5. changes in gross domestic product (GDP)	1. number of passenger 2. cargo and mail	- Compute mean efficiency rating over 88/89 – 96/97 and use it to rank 22 airports before and after privatization.
Salazar De la Cruz (1999)	Year: 1993 – 1995 Size: 16 main Spanish airports serviced mixed domestic and international passenger traffic; range 1 – 20 million passengers	DEA-Output-CRS	1. total economic cost e.g., cost for annual operations, the current costs and the internal interest on the net assets	1. annual passengers 2. total returns 3. returns on infrastructure services 4. operative returns 5. final returns	- Empirically, observe the extent to which input and output contribute to the change in efficiency by visualizing from graph

Table 2.4 List of publications on airport productivity studies using DEA (Continued)

Author(s)	Sample Year	Model	Input	Output	Remark
Sarkis (2000)	Year: 1990 – 1994 Size: 44 major U.S airports	DEA- Input-CRS DEA- Input-VRS	1. operating costs 2. number of airport employees 3. number of gates 4. number of runways	1. operational revenue 2. number of passengers 3. aircraft movements 4. general aviation movements 5. amount of cargo shipped	- Include the following variants 1. Simple cross-efficiency (SXEF) (Doyle and Green, 1994) 2. Aggressive cross-efficiency (AXEF) (Doyle and Green, 1994) 3. Ranked efficiency (RCCR) (Anderson and Peterson, 1993) 4. Radii of classification ranking (GTR) (Rousseau and Semple, 1995) - Perform nonparametric Mann- Whitney U-test to test the differences of efficiency scores between hub/non-hub, MAS/SAS, and snowbelt/non-snowbelt

Table 2.4 List of publications on airport productivity studies using DEA (Continued)

Author(s)	Sample Year	Model	Input	Output	Remark
Adler and Berechman (2001)	Year: 1996 Size: 26 airports in Western Europe, North America and the Far East	DEA-Input-VRS (dual formulation)	<ol style="list-style-type: none"> 1. peak short and medium haul charges 2. inversed number of passenger terminal 3. inversed number of runways 4. distance to the city center 5. minimum connecting time international – international 6. average delay per aircraft movement in minutes 	<p>Three principal components derived from the following five measures of service quality from airlines' perspective</p> <ol style="list-style-type: none"> 1. suitability 2. operational reliability and convenience 3. cost of using airport 4. overall satisfaction and airport quality 5. factual questions with respect to the wave system and demand 	<p>- Survey airport quality of service from airlines rating 14 questions on Likert scale; and due to excessive number of total variables (inputs + outputs), the authors apply Principal Component Analysis (PCA) statistical method to reduce the total number inputs/outputs</p> <p>- Apply super-efficient DEA model (Anderson and Peterson, 1993) to fully rank the airports and report unbound results (infeasibility in primal) for some airports.</p>

Table 2.4 List of publications on airport productivity studies using DEA (Continued)

Author(s)	Sample Year	Model	Input	Output	Remark
Fernandes and Pacheco (2001)	Year: 1998 Size: 35 Brazilian domestic airports	DEA-Non-oriented-CRS	1. mean number of employees 2. payroll expenditure, including direct and indirect benefits 3. operating expenditures 4. apron area 5. departure lounge area 6. number of check-in counters 7. length of curb frontage 8. number of vehicle parking spaces 9. baggage claim area	1. number of passengers, 2. cargo plus mail, 3. operating revenues 4. commercial revenues 5. other revenues	
Martin and Roman (2001)	Year: 1997 Size: 37 Spanish airports	DEA-Output-VRS DEA-Output-CRS	1. labor expense 2. capital expense, including amortization of fixed assets 3. material expense	1. air traffic movements 2. number of passengers 3. tonnage of cargo	- Compute technical efficiency by using reciprocal of efficiency score obtained from solving DEA - Compute scale efficiency - Interpret target output and input slack

Table 2.4 List of publications on airport productivity studies using DEA (Continued)

Author(s)	Sample Year	Model	Input	Output	Remark
Pels, Nijkamp and Rietveld (2001)	Year: 1995 – 1997 (pooled cross- section time series) Size: 34 European airports	Air transport movements (ATM) model DEA- Input-CRS DEA- Input-VRS Air passenger movements (APM) model	1. airport area 2. runway length 3. number of aircraft parking positions at the terminal 4. number of remote aircraft parking positions 1. terminal area 2. number of aircraft parking positions at the terminal 3. number of remote aircraft parking positions 4. number of check-in desks 5. number of baggage claim units	1. Air transport movements (ATM) 1. Air passenger movements (APM)	- Estimate also the stochastic production frontier (see Table 2.2 for the same authors)

Table 2.4 List of publications on airport productivity studies using DEA (Continued)

Author(s)	Sample Year	Model	Input	Output	Remark
Abbott and Wu (2002)	Year: 1989/1990 to 1999/2000 Size: 12 main Australian airports	DEA-Input-CRS	1. number of staffs 2. capital stock 3. runway length	1. number of passengers 2. freight cargo in tons	- Compute Malmquist total factor productivity (TFP) index, - Estimate Tobit regression for explaining variation in Malmquist TFP
	Year: 1998/99 Size: 12 main Australian and 13 other international airports	DEA-Input-CRS	1. number of staffs 2. runway length 3. land area 4. number of aircraft standing areas	1. number of passengers 2. freight cargo in tons	
Fernandes and Pacheco (2002)	Year: 1998 Size: 33 Brazilian major domestic airports	DEA-Output-VRS	1. area of apron 2. area of departure lounge 3. number of check-in counters 4. length of frontage curb 5. number of parking spaces 6. baggage claim area	1. domestic passengers	- Analyze inefficiency level, slacks, potential number of domestic passengers in comparison to demand forecast

Table 2.4 List of publications on airport productivity studies using DEA (Continued)

Author(s)	Sample Year	Model	Input	Output	Remark
Bazargan and Vasigh (2003)	Year: 1996 – 2000 Size: Top 45 U.S. airports, 15 each from large, medium and small hubs (by FAA’s definition) during the study period	DEA-Input-CRS	1. operating expenses 2. non-operating expenses 3. number of runways 4. number of gates including gates with jet ways and other non jet- way gates	1. number of passengers 2. air carrier operations 3. number of commuters, GA and military 4. aeronautical revenues 5. non-aeronautical revenues 6. percentage of on-time operations	- Achieve a full ranking of all airports by introducing a virtual super efficient airport with existing airports so that there will be only one efficient airport. Its inputs and outputs are as follows: - Test the difference among three hub types by non-parametric Kruskal-Wallis test.
Pacheco and Fernandes (2003)	Year: 1998 Size: 35 Brazilian domestic airports	DEA-Input-VRS	1. average number of employees 2. payroll, including direct and indirect benefits 3. operating expenses	1. domestic passengers 2. cargo plus mail 3. operating revenues 4. commercial revenues 5. other revenues,	- Use efficient scores from Fernandes and Pacheco (2002) as physical efficiency score and management efficiency score from this study to create Boston Consultancy Group (BCG) matrix
Pathomsiri and Haghani (2004)	Year: 2000, 2002 Size: 63 airports in multiple airport system worldwide	DEA-Output-VRS	1. land area 2. number of runways 3. area of runways	1. aircraft movements 2. number of passengers	- Perform paired-sample t-test to see if there is significant difference in efficiency scores before and after September-11. - Compute target inputs and outputs for inefficient airports

Table 2.4 List of publications on airport productivity studies using DEA (Continued)

Author(s)	Sample Year	Model	Input	Output	Remark
Pels, Nijkamp and Rietveld (2003)	Year: 1995-1997 (pooled cross- section time series) Size: 34 European airports	Air transport movements (ATM) model DEA- Input-CRS DEA- Input-VRS	1. airport area 2. number of runways 3. number of aircraft parking positions at the terminal 4. number of remote aircraft parking positions	1. Air transport movements (ATM)	- Estimate also the stochastic production frontier (see Table 2.2 for the same authors) - Number of runways is treated as a fixed factor and adopted Banker and Morey (1986) formulation.
		Air passenger movements (APM) model	1. ATM 2. number of check-in desks 3. number of baggage claim units	1. Air passenger movements (APM)	

Table 2.4 List of publications on airport productivity studies using DEA (Continued)

Author(s)	Sample Year	Model	Input	Output	Remark
Sarkis and Talluri (2004)	Year: 1990 – 1994 Size: 44 major U.S. airports	DEA-Input-CRS	1. operational costs 2. number of airport employees 3. number of gates 4. number of runways	1. operational revenue 2. passengers 3. aircraft movements 4. number of general aviation movements 5. total cargo	- Rank airports by mean cross-efficiency scores (AXEF) (Doyle and Green, 1994) - Identify benchmarks by using the hierarchical clustering technique based on correlation coefficients of the columns in the cross-efficiency matrix. The average linkage method is utilized to derive the clusters. Airports in each cluster have a benchmark.
Fernandes and Pacheco (2005)	Year: 1998 and 2001 Size: 58 airports administered by the Brazilian Airport Infrastructure Enterprise, Infraero	DEA-Input-VRS	1. payroll, including direct and indirect benefits 2. operating and other expenses 3. average number of employees	I. Financial performance 1. operating revenues 2. commercial revenues 3. other revenues II. Operating performance 1. passengers embarked plus disembarked 2. tonnage of cargo embarked plus disembarked	

Table 2.4 List of publications on airport productivity studies using DEA (Continued)

Author(s)	Sample Year	Model	Input	Output	Remark
Pathomsiri, Haghani and Schonfeld (2005)	Year: 2000 , 2002 Size: 72 airports in multiple airport system worldwide	DEA- Output-VRS	1. land area 2. number of runways 3. area of runways	1. aircraft movements 2. number of passengers	- Use parametric and nonparametric statistical methods to test the difference of efficiency scores before and after September 11
Pathomsiri, Haghani, Dresner and Windle (2006a)	Year: 2000 - 2002 Size: 72 airports in multiple airport systems worldwide	DEA- Output-VRS	1. land area 2. number of runways 3. area of runways	1. aircraft movements 2. number of passengers	- Estimate Tobit regression model to explain variation in airport productivity

2.3 Data Envelopment Analysis (DEA)

2.3.1 Background

DEA is a relatively new “data oriented” approach for evaluating performance of a set of peer entities called Decision Making Units (DMUs) which convert multiple inputs into multiple outputs. The story of DEA begins with Edwardo Rhodes’s Ph.D. dissertation research at Carnegie Mellon University. The research was to evaluate Program Follow Through – the educational program for disadvantaged students (mainly black and Hispanic) undertaken in U.S. public schools with support from the Federal Government. It was the challenge of estimating relative technical efficiency of the schools involving multiple outputs and inputs, without using the information on prices that resulted in the formulation of the CCR (Charnes, Cooper and Rhodes) ratio form of DEA and the first publication (Charnes, Cooper and Rhodes, 1978). The DEA models use the optimization method of mathematical programming to generalize the Farrell (1957) single-output/input technical efficiency measure to the multiple-output/multiple-input case. Thus DEA began as a new Management Science tool for technical-efficiency analyses of public sector DMUs (Charnes, Cooper, Lewin and Seiford, 1994).

The definition of a DMU is generic and flexible (Cook and Zhu, 2005; Cooper, Seiford, Zhu, 2004). Since the introduction in 1978, researchers in a number of fields have quickly recognized its usefulness and applicability. In recent years, there have been a great variety of applications of DEA in evaluating the performances of many kinds of entities engaged in many different activities in many different contexts in many different countries (Cooper Seiford and Tone, 2000; Cook and Zhu, 2005; Cooper, Seiford and Zhu, 2004). Seiford (1996) provides a bibliography since its first publication in 1978 to

1995. Some textbooks exclusively cover DEA (Cooper, Seiford and Tone, 2000; Zhu, 2003; Ray, 2004; Cooper, Seiford and Zhu, 2004; Cook and Zhu, 2005). From time to time journals publish special issues on DEA theory and applications (Haynes, Stough, and Shroff, 1990; Cooper, Seiford, Thanassoulis and Zanakis, 2004). Emrouznejad (2006) has maintained a website that describes a rich family of DEA models.

DEA opened up possibilities for use in cases which have been resistant to other approaches because of the complex (often unknown) nature of the relationship between the multiple inputs and multiple outputs involving DMUs. DEA requires very few assumptions. It does not need a priori assumption on functional form. This has made DEA applications quickly pervasive. In transportation, DEA has been applied to assess productivity of several activities such as public transit (Kerstens, 1996; Pina and Torres, 2001; Boame, 2004; Boame and Obeng, 2005), railway (Coelli and Perelman, 1999), large-scale distribution systems (Ross and Droge, 2004), ports (Tongzon, 1995; Budria, Diaz-Armas, Navarro-Ibanez and Ravelo-Mesa, 1999; Tongzon, 2001; Itoh, 2002; Turner, Windle and Dresner, 2004), and airlines (Schefczyk, 1993; Scheraga, 2004; Pires Capobianco and Fernandes, 2004). DEA has become a useful analytical tool for productivity study and performance analysis during the past two decades.

In airport sector, researchers started using DEA in the late 1990s. The early works include Gillen and Lall (1997, 1998); Murillo-Melchor (1999); and de la Cruz (1999). Recently, there are a good number of publications using DEA to assess productivity of airports in different regions. Table 2.4 summarizes DEA publications in airport sector. For each study, the Table describes author(s), sample characteristics, analysis period, type of applicable DEA model, as well as set of inputs and outputs. The remark in the last

column notes major extra work beyond application of DEA in those studies. For example, after solving DEA models, Gillen and Lall (1997); Pathomsiri, Haghani, Dresner and Windle (2006a) estimated Tobit regression models for explaining variation in output efficiency scores. Meanwhile, Gillen and Lall (1998) and Abbott and Wu (2001) compute Malmquist index to explain changes of total factor productivity over time.

2.3.2 Model development

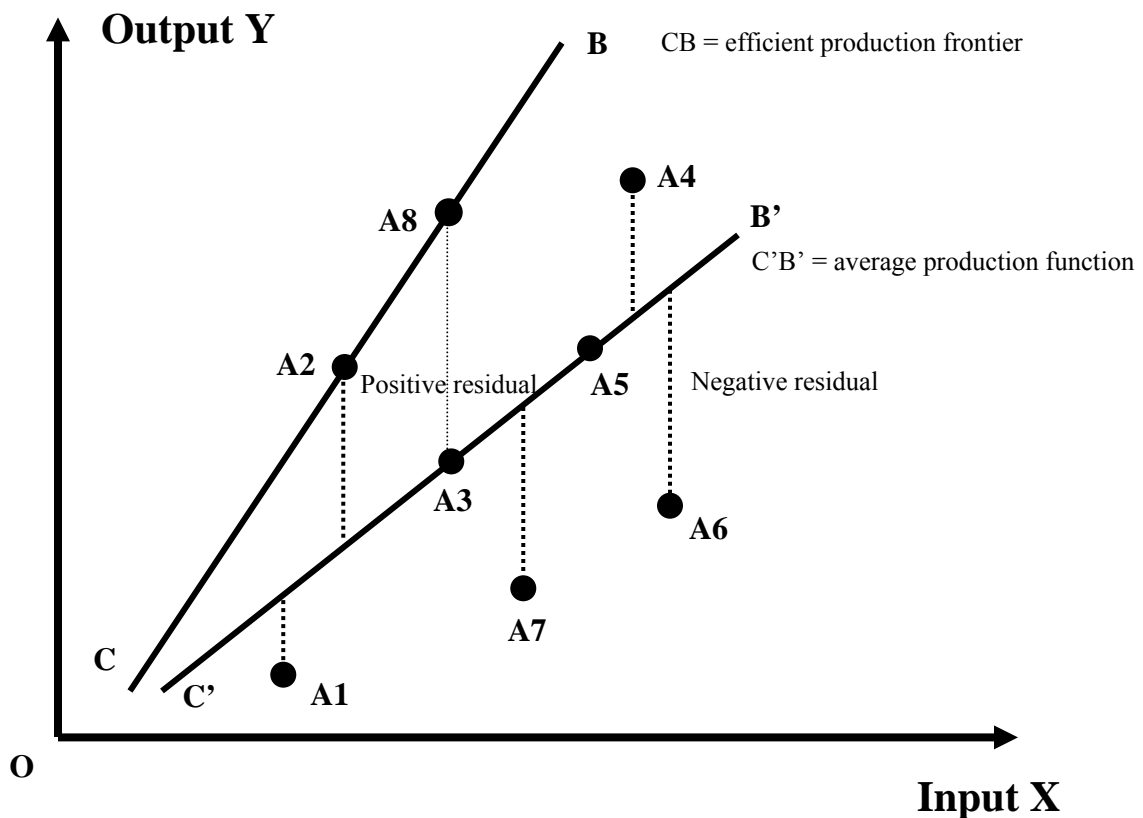


Figure 2.1 Difference between DEA and regression concept

DEA is a methodology directed to frontiers rather than central tendency. Suppose that there is a set of hypothetical airports whose airside operation take only single input X (e.g., runway) and produces single output Y (e.g., aircraft movements). Their input and output measures are scatter plotted in Figure 2.1. If one were to use a regression model to

estimate the production function of this operation, the fitted line would be C'B' which passes through the "cloud" of data points. This regression line basically explains the average production. For airports A1, A6, and A7 this production function gives negative residuals or overestimated production. Meanwhile the fitted line will give positive residuals or underestimated production for airports A2, A4 and A8. The residuals are the portion of production that results from other factors beyond this single output.

Instead of fitting a line to the data, DEA tries to learn from airports that lie above the line (airports with positive residuals). These airports are outliers that provide a good benchmark meaning that for a given input X, there is no other airport producing more Y. An alternative line CB is therefore drawn to represent the maximum possible production function or efficient production frontier that encompasses all airports. Any airports on this frontier are regarded as efficient whereas other airports within the frontier are inefficient. The further an airport is from the frontier, the more inefficient it is. DEA determines the efficient production frontier by estimating the distance for individual airports. Figure 2.2 explains the mechanism.

DEA checks each airport to find out whether it lies on the frontier. Consider airport A3 which is below the frontier CB. Denote a scalar multiplier Φ to current output y_2 for boosting the production to the maximum level at A9 on the frontier. A9 may be viewed as a virtual airport whose input and output levels are the linear combination of airports A2 and A8, i.e., $(\lambda_1 x_1 + \lambda_2 x_2, \lambda_1 y_1, \lambda_2 y_2)$. Intuitively, for efficient airports, i.e., A2 and A8, their multipliers equal to one because they do not need to boost the production any further. All other inefficient airports will have some value depending on how inefficient they are. In real application, the production consists of multiple inputs and

outputs, rather than single input/output as shown in Figure 2.2; therefore it would be impossible to visualize. In this case the multiplier Φ can be estimated by solving the following LP problem:

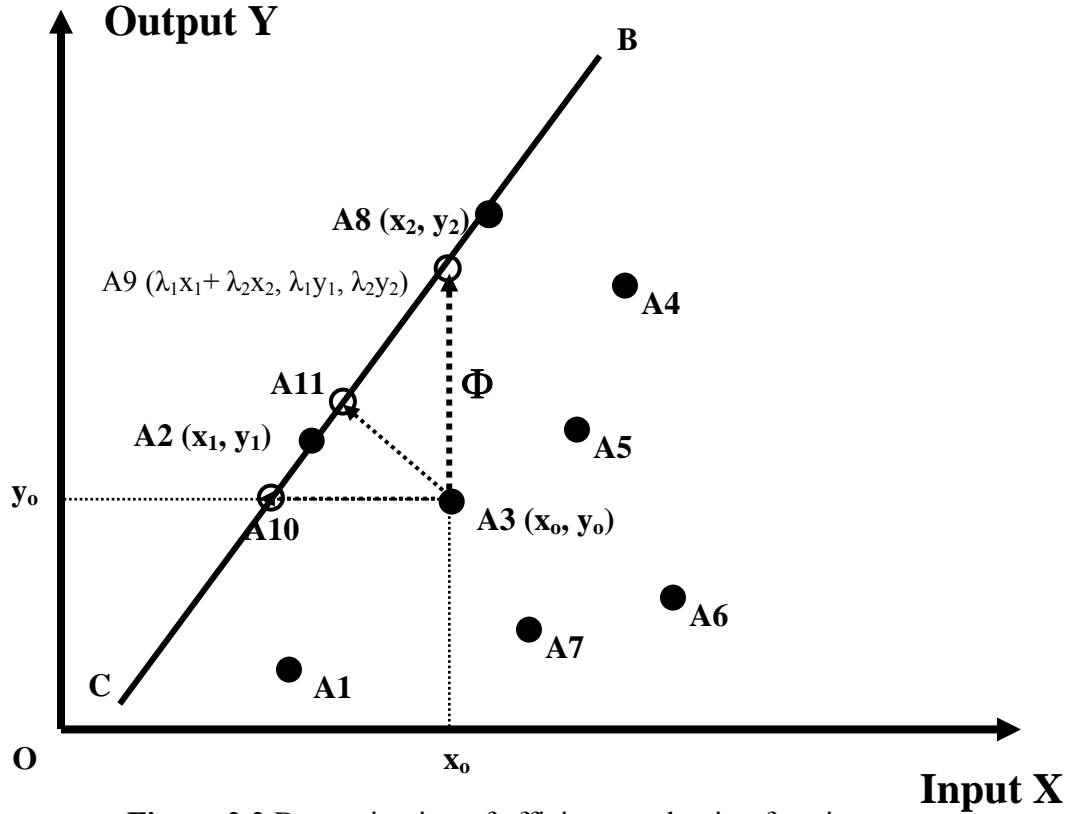


Figure 2.2 Determination of efficient production frontier

$$\begin{aligned}
 & \max \Phi_k \\
 & s.t. \\
 & \sum_{k \in K} \lambda_k y_{km} - s_m^+ = \Phi y_{km}, m = 1, \dots, M, \\
 & \sum_{k \in K} \lambda_k x_{kn} + s_n^- = x_{kn}, n = 1, \dots, N, \\
 & \lambda_k \geq 0, k = 1, \dots, K
 \end{aligned} \tag{2.1}$$

Where k, m and n represent index of airports ($k = 1, 2, \dots, K$), index of outputs ($m = 1, 2, \dots, M$) and index of inputs ($n = 1, 2, \dots, N$) respectively. λ_k is an intensity vector associated with each airport and has k elements. x_{kn}, y_{km} are quantity of input n

and output m of airport k respectively. s_m^+ and s_n^- are output and input slacks respectively. Φ or the output efficiency score is a scalar by which the current output level has to be multiplied in order to reach the frontier. If an airport is on the frontier, solving this LP will result in an optimal objective function $\Phi_k^* = 1$. In other words, it is sufficiently productive and does not need to increase output. Φ is bound by $[1, \infty)$. The efficiency score can be used as a TFP measure. The LP needs to be solved k times, each time for an individual airport.

The LP formulation in (2.1) is known as “Output-Oriented with Constant Return-to-Scale Characterization DEA model”, or in short DEA-Output-CRS hereinafter. As the name implies, the formulation seeks to determine if an airport is on the frontier in the output direction, for a given level of inputs. The analysis provides an assessment of how efficiently the inputs are being utilized. The DEA-Output-CRS has been used by several researchers including Gillen and Lall (1997, 1998); Fernandes and Pacheco (2002); de la Cruz (1999); Martin and Roman (2001); Pathomsiri and Haghani (2004); Pathomsiri, Haghani and Schonfeld (2005); Pathomsiri, Haghani, Dresner and Windle (2006a).

In fact, the inefficiency can be determined in other directions as well. Figure 2.2 shows another two possible directions. The first is in the direction of input, i.e., projecting A3 to the frontier at A10. If this is the case, the corresponding LP formulation is given in (2.2).

$$\begin{aligned}
 & \min \theta_k \\
 & s.t. \\
 & \sum_{k \in K} \lambda_k y_{km} - s_m^+ = y_{km}, m = 1, \dots, M, \\
 & \sum_{k \in K} \lambda_k x_{kn} + s_n^- = \theta x_{kn}, n = 1, \dots, N, \\
 & \lambda_k \geq 0, k = 1, \dots, K
 \end{aligned} \tag{2.2}$$

All notations are the same as defined above. θ_k or the input efficiency score is a scalar by which the current input level has to be multiplied in order to reach the frontier. The LP formulation in (2.2) is known as “Input-Oriented with Constant Return-to-Scale Characterization DEA model”, or in short DEA-Input-CRS hereinafter. The model determines whether there is inefficiency in input, for a given level of output. If an airport is on the frontier, solving this LP will result in an optimal objective function $\theta_k^* = 1$. In other words, the current level of input is probable and does not need to be reduced. θ is bound by (0, 1]. The input efficiency score can be used as a TFP measure. The LP needs to be solved k times, each time for an individual airport. The DEA-Input-CRS has been used by several researchers including Abbott and Wu (2002); Adler and Berechman (2001); Bazargan and Vasigh (2003); Fernandes and Pacheco (2005); Murillo-Melchor (1999); Pacheco and Fernandes (2003); Parker (1999); Pels, Nijkamp and Rietveld (2001, 2003); Sarkis (2000); Sarkis and Talluri (2004); and Yoshida and Fujimoto (2004).

In Figure 2.2 there is another direction which is the shortest possible distance, i.e., projecting A3 to the frontier at A11. In this case DEA does not care about direction. The LP formulation simultaneously expands the output and contracts inputs. The efficiency score indicates inefficiency level in both input and output. The model is called “Non-oriented with Constant Return-to-Scale Characterization DEA model”, or in short DEA-

Non-oriented-CRS. The model is rarely used in airport productivity studies since it is not practical to freely adjust inputs/outputs mix. An airport manager is unlikely to choose the combination of capital inputs (e.g., runway, taxiway, and terminal building) and passenger throughput. Either input or output may be not controllable. It is found that only Fernandes and Pacheco (2001) adopted the DEA-Non-Oriented-CRS to assess the productivity of 35 Brazilian airports. The formulation is not given here, but can be found in several textbooks including Zhu (2003), Ray (2004) and Cooper, Seiford and Zhu (2004).

Regardless of the chosen orientation, there is no effect on the classification of efficient airports because the resulting efficient frontiers are identical. However, it does affect results regarding inefficient airports. Researchers have to justify the choice of orientation. Regarding the use of input orientation, Abbott and Wu (2002) justify by reasoning that “airports have fewer controls over outputs than they do over inputs. The volume of airline traffic is somewhat exogenous to the control of airports’ managers depending as it does mainly on the general level of economic activity, both in the host city and the Australian and international economies more generally.” Meanwhile, Pacheco and Fernandes (2003) justify that they were dealing with Brazilian airports of various sizes.

Martin and Roman (2001) justify the use of output orientation in their assessment of Spanish airports by reasoning that “We think that once an airport has invested in the building of new runways or new terminals, it is difficult for managers to disinvest to save costs, therefore invalidating the input-orientation.” Meanwhile, Fernandes and Pacheco

(2002) argue that the main issue of their analysis is the potential output from organizations with various sizes.

In addition to the CRS frontier type, DEA can be carried out under the assumptions of variable returns to scale by introducing a scale constraint into the model. In VRS frontier type DMUs are not penalized for operating at a non-optimal scale (Banker, 1984; Banker and Thrall, 1992). Ganley and Cubbin (1992) consider the CRS frontier type as the long-term view as opposed to short-term view for VRS frontier. Martin and Roman (2001) argue that due to the existence of different scale airports in Spain, a VRS frontier should be used. Nonetheless they estimate also the CRS model. Parker (1999) argues that given the variation in the size of the airports in his dataset, VRS is the more realistic assumption than CRS. Murillo-Melchor (1999) however, argues that scale efficiency requires that the production size corresponds to the long-run. For this reason, this efficiency is assessed with respect to the technology of a long-run model i.e., constant returns to scale. Table 2.5 summarizes some important DEA models that have been used in previous airport productivity studies. The efficient targets in the last row compute the probable levels of input and outputs for those inefficient airports.

2.4 Discussion

The data availability on prices tends to limit the applicability of parametric approach. Literature review clearly indicates that non-parametric approach such as index number and DEA are more widely used by researchers. During the past decade, many researchers have adopted DEA to assess productivity of airports in different regions around the world.

Table 2.5 Summary of DEA models

Frontier type	Input-oriented	Output-oriented
CRS	$\min \theta$ $s.t.$ $\sum_{k \in K} \lambda_k y_{km} - s_m^+ = y_{km}, m = 1, \dots, M,$ $\sum_{k \in K} \lambda_k x_{kn} + s_n^- = \theta x_{kn}, n = 1, \dots, N,$ $\lambda_k \geq 0, k = 1, \dots, K$	$\max \Phi$ $s.t.$ $\sum_{k \in K} \lambda_k y_{km} - s_m^+ = \Phi y_{km}, m = 1, \dots, M,$ $\sum_{k \in K} \lambda_k x_{kn} + s_n^- = x_{kn}, n = 1, \dots, N,$ $\lambda_k \geq 0, k = 1, \dots, K$
VRS	Add $\sum_{k \in K} \lambda_k = 1$	
NIRS	Add $\sum_{k \in K} \lambda_k \leq 1$	
NDRS	Add $\sum_{k \in K} \lambda_k \geq 1$	
Efficient target	$\hat{x}_{kn} = \theta x_{kn} - s_n^-, n = 1, \dots, N$ $\hat{y}_{km} = y_{km} + s_m^+, m = 1, \dots, M$	$\hat{x}_{kn} = x_{kn} - s_n^-, n = 1, \dots, N$ $\hat{y}_{km} = \Phi y_{km} + s_m^+, m = 1, \dots, M$

Based on the review, it can be observed that previous studies assess productivity by only looking at desirable outputs such as passengers, aircraft movements, cargo and revenues. Inherently in the nature of airport operations, there are always undesirable byproducts being produced such as delays, mishandled baggage and accidents. In addition, airport operations also create externalities, notably noise and pollution. These byproducts may also be considered to be airport outputs, although undesirable, and they

are major concerns of the aviation industry. All airport stakeholders wish to minimize these undesirable outputs, or at least keep them at acceptable levels. Accounting for undesirable outputs in decision making is therefore, a goal of managers in the aviation industry. However, none of them considers joint production of desirable and undesirable outputs in the assessment, except Yu (2004). In that study, the author considered aircraft noise (in 1000 New Taiwan dollars) as the lone undesirable output. There are several limitations in this work. It is not clear how noise is measured and transformed into monetary unit. The sample size of 14 Taiwanese airports is too small when compare to the number of inputs (5) and outputs (3) measures. In DEA framework, the sample size should be much greater than number of inputs times outputs (Cooper, Seiford and Tone, 2000: page 252). Otherwise the discriminatory power will be deteriorated. That is the reason why Yu (2004) reports many efficient airports. Furthermore, other major undesirable outputs are excluded. In the US, delays are a major concern of air services. BTS (2006) routinely records on-time performance of flights and delays. In Europe, the situation about air traffic control is getting worse. In 2000, around 30% of flights experienced delays more than 15 minutes and air traffic control was the most important causes of delays (Martin and Roman, 2001).

In fact some researchers have discussed about undesirable outputs but did not address them. In their ad-hoc Tobit regression models, Gillen and Lall (1997) noted that greater noise restriction tend to lower movement performance. To clean up noise, airports need to trade their movements low. Some researchers have pointed out the association between efficient airports and delays. Salazar de la Cruz (1999) observed that those airports that define the frontier show very high level of utilization, confirmed by further

congestion problems and expansion works. Furthermore, he suggests that it will be more prudent to consider the inefficiencies associated with level of usage, climate conditions, economy of design, construction or quality level including delays, etc. Especially, the necessity to consider the impact of capacity and delays jointly requires the introduction of specific behavioral models for each airport, information for which is not easily available.

Based on previous work (Adler and Berechman, 2001; Bazargan and Vasigh, 2003; Fernandes and Pacheco, 2002; Gillen and Lall, 1997, 1998; Martin and Roman, 2001; Pacheco and Fernandes 2003; Pathomsiri and Haghani, 2004; Pathomsiri, Haghani and Schonfeld, 2005; Pathomsiri, Haghani, Dresner and Windle, 2006a; Pel, Nijkamp and Rietveld, 2001, 2003; Sarkis, 2000; Sarkis and Tulluri, 2004), DEA results tend to identify busy airports as efficient. Frequently, these efficient airports are also congested. It may be that one airport creates greater numbers of delayed flights than another, but produces the same level of desirable outputs per unit of input. Unless delays are taken into account, both airports would show the same productivity level.

Consideration of undesirable outputs is not as straightforward as desirable outputs, but quite problematic. In DEA literature, there is a general guideline for distinguishing between input and output variables. If the lower level of measure is better, it should be classified as an input; but if the higher quantity is desirable, that variable is classified as an output. This is not true in airport operation where the higher quantity of undesirable outputs such as noise, pollution, delays, and accident are not desirable. Moreover, these outputs are not inputs in airport operation either. Even so, Adler and Berechman (2001) consider delay as an input.

Estimation is also an issue. The limitation lies in the mathematical mechanism for determining if an airport is on the efficient frontier. Using DEA-Output orientation would seek to maximize the expansion of all outputs, rather than maximize only the desirable outputs and minimize the undesirable. In reality, an airport manager never wishes to expand both number of passengers and delays simultaneously. The ad-hoc DEA is not applicable either (Färe and Grosskopf, 2004a, 2004b; Seiford and Zhu, 2002, 2005). The issue will need a special mathematical formulation.

As a result, it is a very challenging task to analyze airport productivity where there is joint production of desirable and undesirable outputs. Accounting for both types of outputs should provide a more complete measure of airport productivity. Furthermore, consideration of undesirable outputs such as reduction in delays may lead to different evaluation which in turn results in different management policy. For example, it could affect the time when expansions and new facilities must be operated. This pioneer research will address this problem and attempt to point out the effects of joint consideration of desirable and undesirable outputs.

It should be noted that all studies that are categorized as TFP are termed as such because they consider more than one input and output. It is virtually impossible to consider all of the factors in a productivity study. Since this dissertation also considers multiple important inputs and outputs, it can also be considered as a TFP study.

CHAPTER 3

RESEARCH METHODOLOGY

This chapter presents the methodology that will be used to assess the productive efficiency of airport operation with joint consideration of both desirable and undesirable outputs. The methodology is based on the production theory from economics discipline. The chapter starts off with the characterization of production technology in order to represent the relationship between input and output measures. The traditional axiom of production theory i.e., the distance function is then introduced. Taking this as a building block an optimization model, called the directional output distance function, is developed. It is of a non-parametric type applicable for modeling production system with multiple inputs and outputs and provides measures of performance without appealing to prices. Finally, the productivity index number is devised for use in analyzing productivity changes over time.

3.1 Characterization of production possibility set

In environmental economics one often wishes to distinguish between desirable ($y \in R_M^+$) and undesirable ($b \in R_J^+$) outputs. In the production context the former output is typically a marketable goods and the latter is often not marketed, but rather a byproduct which may have deleterious effects on the environment or human health, and therefore its disposal is often subject to regulation. As a result, it should be useful to explicitly model the effects of producing both types of outputs, taking into account their characteristics and their interactions (Färe and Grosskopf, 2004b).

Let's consider a production process that desirable and undesirable outputs may be jointly produced, i.e., b is a byproduct of the production of y . Here, the application is an airport operation that processes throughputs of passengers, aircraft movements and cargo by using its infrastructure such as land, runway, and terminal. In this case, the desirable or marketable outputs are number of passengers, movements and amount of cargo transported. There is also undesirable byproduct, i.e., delays (others may include noise and pollution). The basic problem is that given technology, producing these throughputs means simultaneously producing delays even though their production is undesirable.

The production technology T describes the possible transformations of inputs ($x \in R_N^+$) into ($y \in R_M^+$) and undesirable ($b \in R_J^+$) outputs. The production possibility set is defined as a set of desirable and undesirable outputs that can be produced from a given level of inputs. This set is represented by:

$$P(x) = \{(y, b) : x \text{ can produce } (y, b)\} \tag{3.1}$$

3.2 Output distance function

For the sake of illustration, assume that airport operation produces only two desirable outputs y_1 and y_2 (which may be passengers and aircraft movements) from a given input vector. Figure 3.1 shows a hypothetical output possibility set. Note that the true shape of the set is unknown. The frontier of the set is defined as the output vector that cannot be increased by a scalar multiple without leaving the set. In the Figure, the frontier represents efficient combinations of outputs y_1 and y_2 . However, not all airport operations are efficient; therefore there must be an inefficient airport that lies below the efficient frontier. The basic idea in distinguishing efficient airports from inefficient ones

is to determine how far the current operations are from the frontier. In Figure 3.1, airports A and B are right on the frontier; hence obviously are efficient airports. Meanwhile, airport C is away from the frontier by the distance BC or AC depending on the direction of measurement. As a result, airport C is not efficient.

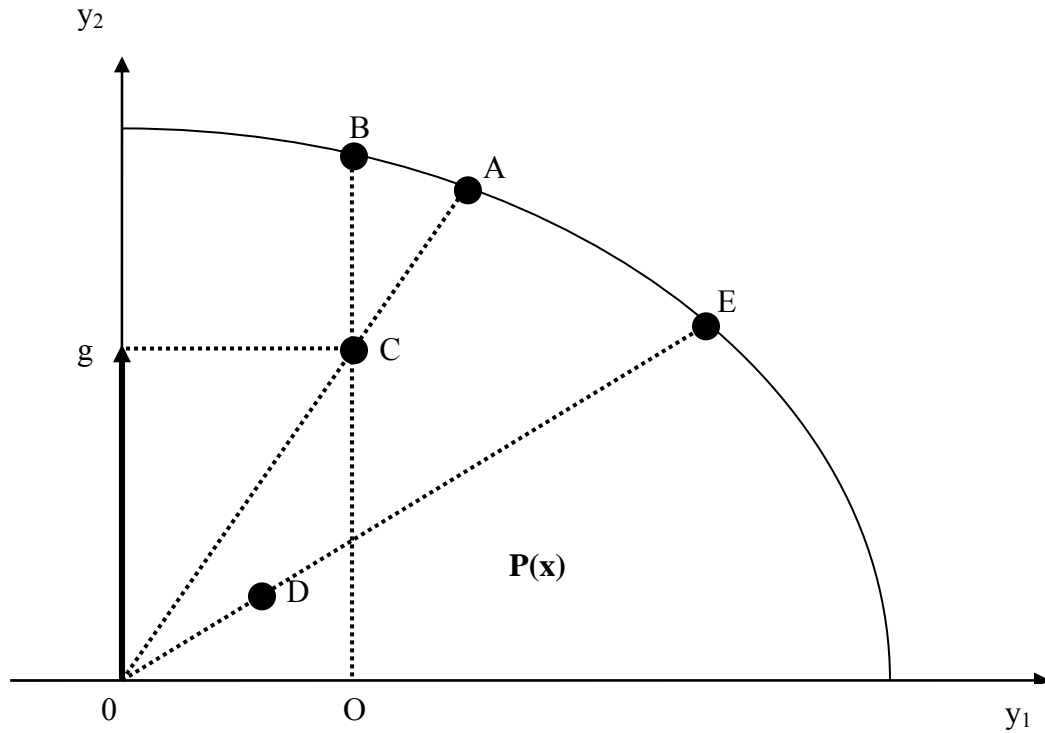


Figure 3.1 Output possibility set and distance functions

Shephard's output distance function (Shephard, 1970) can be used to determine how far an airport is from the frontier. It is defined as the ratio of actual output to maximum potential output and equals to the reciprocal of Farrell's output technical efficiency measure (Farrell, 1957). For any airport, the Shephard's output distance function is:

$$\bar{D}_o(x, y) = \inf\{\Phi : (x, \frac{y}{\Phi}) \in P(x)\} \quad (3.2)$$

$$= \left[\sup \left\{ \Phi : \left(x, \frac{y}{\Phi} \right) \in P(x) \right\} \right]^{-1} \quad (3.3)$$

For airport C in Figure 3.1, $\bar{D}_c(x, y) = \frac{OC}{OA}$. This is a measure of how far the operation of airport C is from the frontier. The function is equal to one for all efficient airports and less than one for inefficient ones. The higher value of distance function indicates higher operational efficiency. The reciprocal of the output distance function $\left(\frac{OA}{OC}\right)$ or the Farrell measure gives the maximum proportional expansion in all outputs that is feasible given inputs. The distance function completely characterizes the production technology T , because as long as $y \in P(x) \Leftrightarrow \bar{D}_o(x, y) \leq 1$ (Färe, Grosskopf, Norris and Zhang (1994b); Färe and Primont, 1995).

However, the generalization of the output distance function in (3.2) to include undesirable output by simply redefining it as $\bar{D}_o(x, y, b) = \inf \left\{ \Phi : \left(x, \frac{y}{\Phi}, \frac{b}{\Phi} \right) \in P(x) \right\}$ would not be meaningful since it would mean proportionate expansion of undesirable and desirable outputs as much as possible, without crediting the reduction of undesirables. In assessing productive efficiency of airports where there is joint production of desirable and undesirable outputs, this is not well-applicable. A rational airport manager should aim at maximizing only desirable, but minimizing undesirable outputs.

3.3 Directional output distance function

Due to the existence of both desirable and undesirable outputs in the output possibility set (3.1), the Shephard's output distance function needs to be modified so that the efficiency measure will be able to credit for expansion of desirable and reduction of

undesirable outputs. First necessary notations are formally defined. Let $y \in R_M^+$ denote a vector of desirable outputs, $b \in R_J^+$ denote a vector of undesirable outputs, and $x \in R_N^+$ denote a vector of inputs. In airport context, K airports with (x_k, y_k, b_k) are examined.

The output possibility set $P(x) = \{(y, b) : x \text{ can produce } (y, b)\}$ in (3.1) satisfies certain axioms laid out by Shephard (1970), namely:

Property 1 $P(0) = \{0,0\}$

Property 2 $P(x)$ is convex and compact for each $x \in R_N^+$

Property 3 $(y, b) \in P(x)$ and $(y', b) \leq (y, b)$ imply $(y', b) \in P(x)$

Property 4 $P(x) \supseteq P(x')$ implies $x \geq x'$

Property 1 states that zero inputs essentially yield zero outputs and any non-negative input yields at least zero output. Sometimes this property is called a condition of no free lunch. Property 2 requires that only finite output should be produced given finite inputs. Property 3 imposes strong or free disposability of desirable outputs which means that it allows any desirable outputs to be disposed costlessly and still remain in $P(x)$. In other words, the disposal of any output can be achieved without incurring any costs in term of reducing the production of other outputs. Property 4 imposes strong or free disposability of inputs. The inputs are also allowed to be disposed costlessly. It also implies that an increase in any one input does not reduce the size of $P(x)$.

Although in production theory it is common to assume that outputs are strongly disposable, it may not be appropriate for production technologies such as present airport operation in which undesirable outputs such as delays and noise cannot be costlessly

disposed. Under regulated environment, an airport is forced to clean up its undesirable outputs or to reduce its levels. Desirable and undesirable outputs should be treated asymmetrically in terms of their disposability characteristics (Zaim, 2005). Even in the absence of regulations, increased environmental consciousness from stakeholders still require careful treatment of undesirable outputs as weakly disposable. To model the idea that there is a cost to reducing undesirable outputs, the next property is assumed.

Property 5 Weak disposability between desirable and undesirable outputs: If $(y, b) \in P(x)$ and $0 \leq \theta \leq 1$, then $(\theta y, \theta b) \in P(x)$.

Property 5 implies that if undesirables are to be decreased, then the desirable outputs must also be decreased, holding inputs x constant. In other words, both desirable and undesirable outputs may be proportionally contracted, but undesirable outputs cannot, in general, be freely disposed. It models the idea that there is a cost to ‘cleaning up’ undesirable outputs. In the airport operation context, it implies that fewer delays can be achieved by letting an airport to service fewer aircraft movements.

Finally, to recognize the nature of joint production of desirable and undesirable outputs, the following property is assumed:

Property 6 Null-jointness, if $(y, b) \in P(x)$, and $b = 0$, then $y = 0$.

This property states that if an output vector (y, b) is feasible and there are no undesirable outputs produced, then under the null-jointness only zero desirable output can be produced. Equivalently, if some positive amount of the desirable output is produced then undesirable output must also be produced. In our airport operation context, null-jointness implies that where there are aircraft movements, there must be some delayed

flights which could be occurred by any cause (e.g., air carrier, extreme weather, non-extreme weather conditions, airport operations, late-arrival aircraft, security, human error, and accident).

There are several ways of integrating the above six properties into the representation of output possibility set, including parametric and nonparametric approaches. The focus here is on the nonparametric model using DEA. The representation of output set is in the form of piecewise linear. Based on the six properties, the production technology for an individual airport k or $P(x_k)$ may be represented by the following output set:

$$P(x_k) = \{(y, b) : \tag{3.4}$$

$$\begin{aligned} \sum_{k \in K} \lambda_k y_{km} &\geq y_{km}, m = 1, \dots, M, \\ \sum_{k \in K} \lambda_k b_{kj} &= b_{kj}, j = 1, \dots, J, \\ \sum_{k \in K} \lambda_k x_{kn} &\leq x_{kn}, n = 1, \dots, N, \\ \lambda_k &\geq 0, k = 1, \dots, K \} \end{aligned}$$

The constraints for the undesirable outputs $b_j, j = 1, \dots, J$ are equality constraints, which under the constant returns to scale models the idea that these outputs are not freely disposable. Meanwhile free disposability of desirable outputs $y_m, m = 1, \dots, M$ and inputs $x_n, n = 1, \dots, N$ are allowed by using the inequalities in their respective constraints. λ_k is an intensity vector.

Figure 3.2 represents the construct of $P(x)$ from four hypothetical airports i.e., A, B, C, and D. These airports are assumed to use the same amount of inputs, x , but produce

different amounts of desirable output, y and undesirable output, b . Since the linear programming of DEA approach is being used to estimate the output distance function, $P(x)$ is drawn as piecewise linear rather than smooth curve as in Figure 3.1. The output possibility set, $P(x)$, is bounded by $0ABCD0$. Airports A, B, and C form an efficient frontier.

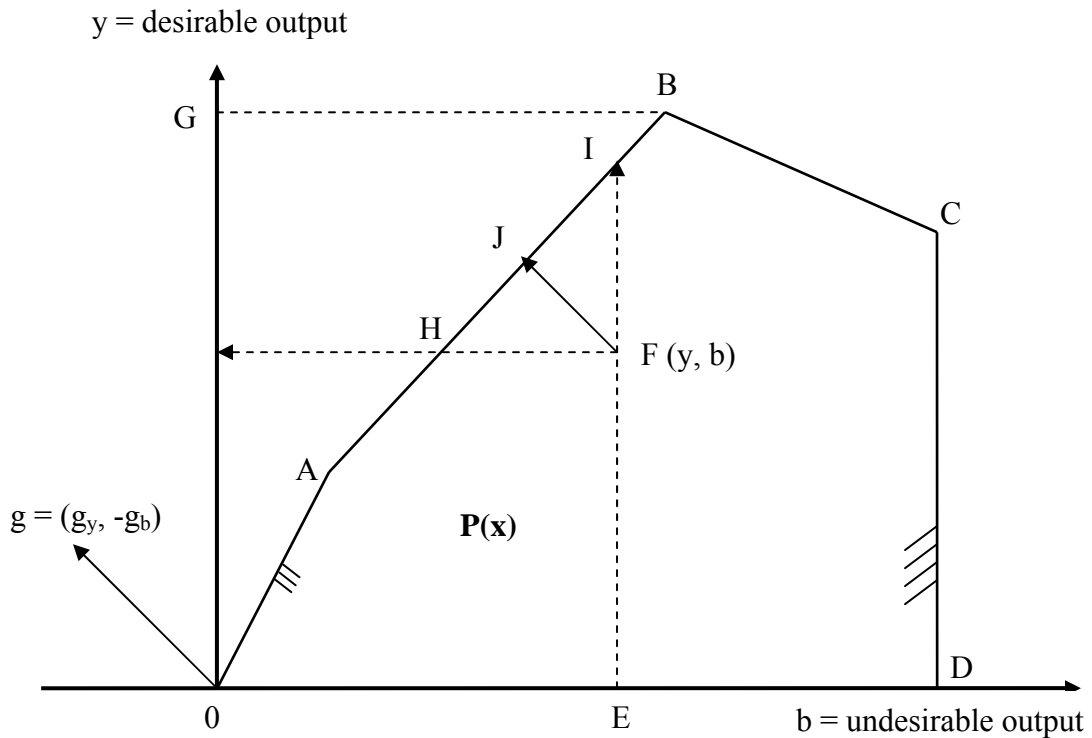


Figure 3.2 Graphical illustration of directional output distance function concept

This figure illustrates how the assumptions are used in the construct. The origin $(0,0)$ is included in $P(x)$ because of the null-jointness assumption. The assumption of weak disposability implies that for any point on or inside $P(x)$, a proportional contraction in both (y,b) is feasible. The vertical line segment CD occurs because of strong disposability between desirable outputs. The negative slope portion BC is possible because sometimes traffic may be blocked due to a long queue of delayed flights; hence

reducing throughput. Note that if undesirable outputs are ignored, $P(x)$ will be the area bounded by 0GBCD0.

Next, the interest is to assess the level of inefficiency for all airports which will tell how far each airport is from the efficient frontier. For airport F, the distance should be measured along the diagonal line FJ or in the direction of vector $g = (g_y, -g_b)$. This measurement is justified on the premise that it seeks to maximize the expansion of desirable outputs and contraction of undesirable outputs simultaneously. The directional output distance function is then formulated as follows:

$$\vec{D}_0(x, y, b; g_y, -g_b) = \sup\{\beta : (y + \beta g_y, b - \beta g_b) \in P(x)\} \quad (3.5)$$

To assess the level of inefficiency for an individual airport, the following linear programming problem is solved:

$$\begin{aligned} & \max \beta \\ & s.t. \\ & \sum_{k \in K} \lambda_k y_{km} \geq y_{km} + \beta g_y, m = 1, \dots, M, \\ & \sum_{k \in K} \lambda_k b_{kj} = b_{kj} - \beta g_b, j = 1, \dots, J, \\ & \sum_{k \in K} \lambda_k x_{kn} \leq x_{kn}, n = 1, \dots, N, \\ & \lambda_k \geq 0, k = 1, \dots, K \end{aligned} \quad (3.6)$$

The selection of a directional vector $g = (g_y, -g_b)$ is rather flexible. For example, using $g = (0, b)$ implies that the level of inefficiency is measured along the horizontal line FH or projecting airport F to the frontier at H. Meanwhile, using $g = (y, 0)$ yields the projection on the frontier at I. Using $g = (1, -1)$ gives the same weight to both desirable and undesirable outputs. In this study, the vector $g = (y, -b)$ will be used, which means

that the projected direction depends on individual airport's outputs. The linear programming in (3.6) is then rewritten as (3.7).

$$\begin{aligned}
 & \max \beta \\
 & s.t. \\
 & \sum_{k \in K} \lambda_k y_{km} \geq (1 + \beta)y_{km}, m = 1, \dots, M, \\
 & \sum_{k \in K} \lambda_k b_{kj} = (1 - \beta)b_{kj}, j = 1, \dots, J, \\
 & \sum_{k \in K} \lambda_k x_{kn} \leq x_{kn}, n = 1, \dots, N, \\
 & \lambda_k \geq 0, k = 1, \dots, K
 \end{aligned} \tag{3.7}$$

The directional output distance function $\vec{D}_0(x, y, b; g_y, -g_b)$ or an optimal β takes the minimum value of zero when it is not possible to expand the desirable outputs and contract undesirable outputs. This means that the airport is efficiently producing at the maximum possible outputs. To assess the productivity of K airports, the linear programming in (3.7) is solved K times, once for each individual airport. Thereafter, the optimal β_k will be called a efficiency score. A higher value of β_k indicates a *lower* level of efficiency. As a result, it can also be used to rank the performance of airports.

The terms $(1 + \beta)y_{km}$ plus the corresponding output slacks and $(1 - \beta)b_{kj}$ in (3.7) give the projection of desirable and undesirable outputs onto the frontier. For an efficient airport with $\beta = 0$, the terms are simply (y_{km}, b_{kj}) or the current level of outputs. For inefficient airports, these terms represent the maximum possible production outputs or highest potential outputs that an airport could have produced. The results may provide benchmarks for airports to improve operational efficiency. However, as is shown in

Chapter 5, the selection of an appropriate set of outputs is crucial to the reasonableness of the benchmark.

In order to relate the Shephard's output distance function and the directional output distance function, let $g = (y, b)$, then through (3.5), it becomes:

$$\begin{aligned}
 \vec{D}_o(x, y, b; y, b) &= \sup\{\beta : (D_o(x, (y, b) + \beta(y, b)) \leq 1\} \\
 &= \sup\{\beta : (1 + \beta)D_o(x, y, b) \leq 1\} \\
 &= \sup\{\beta : \beta \leq \frac{1}{D_o(x, y, b)} - 1\} \\
 &= \frac{1}{D_o(x, y, b)} - 1
 \end{aligned} \tag{3.8}$$

The expression in (3.8) shows that Shephard's output distance function is a special case of the directional output distance function. The relation between the two can be written as:

$$\vec{D}_o(x, y, b; y, -b) = \frac{1}{D_o(x, y, b)} - 1 \tag{3.9}$$

or equivalently,

$$D_o(x, y, -b) = \frac{1}{1 + \vec{D}_o(x, y, b; y, -b)} \tag{3.10}$$

3.4 Malmquist productivity index with the presence of undesirable outputs

The concept of Malmquist productivity index was first introduced by Malmquist (1953) to compare the input of a production unit at two different points in time in terms of the maximum factor by which the input in one period could be decreased such that the

production unit could still produce the same output level of the other time period. The idea leads to the Malmquist input index. It has further been studied and developed in the non-parametric framework by several authors. See for example, among others, Caves, Christensen and Diewert (1982), Färe, Grosskopf, Lindgren and Roos (1994), Färe R., Grosskopf S., Norris M., Zhang Z. (1994) and Färe, Grosskopf and Roos (1998). It is an index representing the Total Factor Productivity (TFP) growth of a decision making unit (DMU), in that it reflects progress or regress in efficiency along with progress of the frontier technology over time under multiple inputs and multiple outputs framework.

Given panel data, the Malmquist index evaluates the productivity change of an airport between two time periods. It is defined as the product of “Catch-up” and “Frontier-shift” terms. The catch-up (or recovery) term relates to the degree that an airport attains for improving its efficiency, while the frontier-shift (or innovation) term reflects the change in the efficient frontier surrounding the airport between the two time periods.

Suppose that undesirable outputs are ignored. To analyze change of productivity over time, (x, y) is superscripted with corresponding time period. Then (x^t, y^t) and (x^{t+1}, y^{t+1}) are measures of inputs and outputs in period t and $t+1$ respectively. From time t to $t+1$ operational efficiency of airport k may change or (and) the frontier may shift. The output-oriented Malmquist productivity index using period t as the base period is the following (Caves, Christensen and Diewert, 1982).

$$M_o = \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \right] \quad (3.11)$$

Alternatively, by using period $t+1$ as the base period, the output-oriented Malmquist productivity index can be written as follows

$$M_o = \left[\frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^t, y^t)} \right] \quad (3.12)$$

In order to avoid choosing an arbitrary frontier as reference, Färe, Grosskopf, Lindgren, and Roos (1994) suggest using the geometric average of the two indexes above. The resulting index is

$$M_t^{t+1} = \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^t, y^t)} \right]^{1/2} \quad (3.13)$$

An alternative way of writing the Malmquist total factor productivity index is:

$$M_t^{t+1} = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})} \frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)} \right]^{1/2} \quad (3.14)$$

Where the ratio outside the bracket measures the change in relative efficiency (i.e., the change in how far observed production is from maximum potential production) between period t and $t+1$. The geometric mean of the two ratios inside the bracket captures the shift in technology between the two periods evaluated at x^t and x^{t+1} , that is

$$\text{Efficiency change (EFFCH)} = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \quad (3.15)$$

$$\text{Technical change (TECHCH)} = \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})} \frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)} \right]^{1/2} \quad (3.16)$$

Although the Malmquist index can in principal deal with undesirable outputs since it does not require knowledge on prices, the distance functions on which it is based

do not credit an airport for reducing level of undesirable outputs. Chung, Färe, and Grosskopf (1997) defined an output-oriented Malmquist-Luenberger (ML) productivity index that is comparable to the Malmquist index. Take undesirable outputs into consideration, (x^t, y^t, b^t) and $(x^{t+1}, y^{t+1}, b^{t+1})$ are measures of inputs, desirable and undesirable outputs in t and $t+1$ respectively. If the directional vector $g^t = (y^t, -b^t)$ and $g^{t+1} = (y^{t+1}, -b^{t+1})$ are chosen in corresponding periods, the output-oriented Malmquist-Luenberger productivity index is:

$$ML_t^{t+1} = \left[\frac{(1 + \bar{D}_o^t(x^t, y^t, b^t; y^t, -b^t))}{(1 + \bar{D}_o^t(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}))} \frac{(1 + \bar{D}_o^{t+1}(x^t, y^t, b^t; y^t, -b^t))}{(1 + \bar{D}_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}))} \right]^{1/2} \quad (3.17)$$

Here \bar{D}_o^{t+1} means that the reference technology is constructed based on data from period $t+1$ and the data being evaluated is included in the parentheses with its associated time period; for example (x^t, y^t, b^t) would mean that the data to be evaluated are from period t . The directional vector g is time dependent. The definition is such that when the directional vector g is (y, b) rather than $(y, -b)$, the Malmquist-Luenberger index coincides with the Malmquist index.

The Malmquist-Luenberger measure indicates productivity improvements if its value is greater than one. The value of less than one indicates decreases in productivity. In other words, it means that with the same amount of inputs as in period $t+1$, the greater quantity of outputs is produced as in period t (Murillo-Melchor, 1999). The productivity remains unchanged if M_o is unity. Similar to the case of Malmquist, the Malmquist-Luenberger index can also be decomposed into two components, namely.

$$MLEFFCH_t^{t+1} = \frac{1 + \bar{D}_o^t(x^t, y^t, b^t; y^t, -b^t)}{1 + \bar{D}_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})} \quad (3.18)$$

$$MLTECHCH_t^{t+1} =$$

$$\left[\frac{(1 + \bar{D}_o^{t+1}(x^t, y^t, b^t; y^t, -b^t)) (1 + \bar{D}_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}))}{(1 + \bar{D}_o^t(x^t, y^t, b^t; y^t, -b^t)) (1 + \bar{D}_o^t(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}))} \right]^{1/2} \quad (3.19)$$

The product of (3.17) and (3.18) equals to ML_t^{t+1} . The decomposition makes it possible to measure the change of technical efficiency and the movement of the frontier for a specific airport. Equation (3.18) measures the magnitude of technical efficiency change between periods t and $t + 1$. The value of less than 1 indicates regress in technical efficiency. In other words, given a level of inputs, the same average output of all samples would have lead to produce more efficiently in period $t + 1$ than in period t (Murillo-Melchor, 1999). Meanwhile the value greater than 1 indicates improvements. The technical efficiency remains unchanged if the value is unity. The second term measures the shift of frontier between periods t and $t + 1$.

Alternatively, Färe, and Grosskopf (2004b) construct another productivity index that has an additive structure, i.e., in terms of differences rather than ratios of Malmquist-Luenberger ratio indexes in (3.17) – (3.19). The index is an output-oriented version of The Luenberger Productivity index introduced by Chambers (1996). Specifically, the index is:

$$L_t^{t+1} = \frac{1}{2} [\bar{D}_o^{t+1}(x^t, y^t, b^t; y^t, -b^t) - \bar{D}_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})]$$

$$+ \bar{D}_o^t(x^t, y^t, b^t; y^t, -b^t) - \bar{D}_o^t(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}) \quad (3.20)$$

Following the idea of Chambers, Färe, and Grosskopf (1996) the Luenberger productivity index can be additively decomposed into an efficiency change and a technical change component,

$$LEFFCH_t^{t+1} = \bar{D}_o^t(x^t, y^t, b^t; y^t, -b^t) - \bar{D}_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}) \quad (3.21)$$

and

$$\begin{aligned} LTECHCH_t^{t+1} = & \frac{1}{2} \left[\bar{D}_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}) - \bar{D}_o^t(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}) \right. \\ & \left. + \bar{D}_o^{t+1}(x^t, y^t, b^t; y^t, -b^t) - \bar{D}_o^t(x^t, y^t, b^t; y^t, -b^t) \right] \quad (3.22) \end{aligned}$$

respectively. The sum of these two components equals the Luenberger productivity index. The index and its components signal improvements with values greater than zero, and declines in productivity with values less than zero. As usual, selection of the directional vector is flexible. If the vector $g = (y, -b)$ is chosen, i.e., choosing the observed desirable and (negative) undesirable output vector to determine the direction, then each airport may be evaluated in a different direction, i.e., in its own direction. This is just typically the case for Shephard type distance functions.

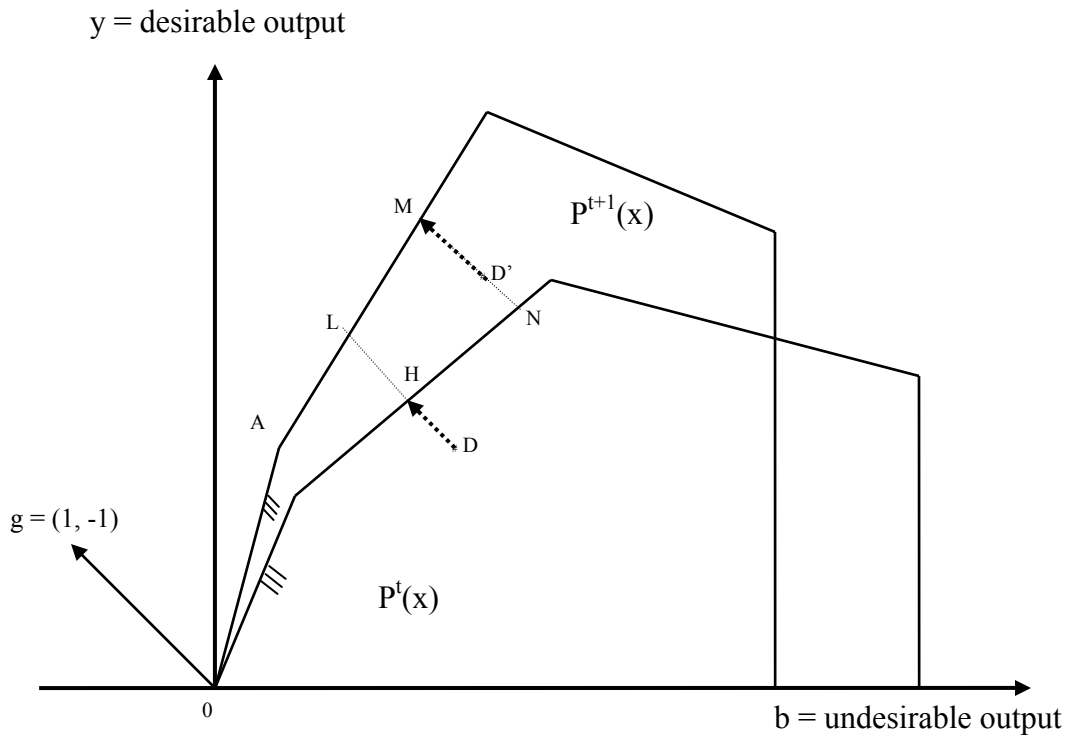


Figure 3.3 The Luenberger productivity indicator

Figure 3.3 illustrates how the Luenberger productivity indicator is constructed. For simplicity, it is assumed that inputs are the same in period t and $t+1$ and are represented by $x = x^t = x^{t+1}$. Without loss of generality, a directional vector $g = (1,1)$ is assumed and illustration is for the case of technological progress (the frontier shifts to the left at period $t+1$). Given $g = (1,1)$, the directional output distance function is an estimate of the simultaneous unit expansion in the desirable output and unit contraction in the undesirable output. An airport is observed to produce at point D in period t and at D' in period $t+1$. If the airport was to eliminate technical inefficiency it could operate at H in period t and at M in period $t+1$. The Luenberger efficiency change indicator is

$$LEFFCH_t^{t+1} = \frac{DH}{og} - \frac{D'M}{og} \quad \text{and the Luenberger technical change indicator is}$$

$$LTECHCH_t^{t+1} = \frac{1}{2} \left[\frac{DL}{og} - \frac{DH}{og} + \frac{D'M}{og} - \frac{D'N}{og} \right] = \frac{1}{2} \left[\frac{HL}{og} + \frac{NM}{og} \right]. \quad \text{By construction,}$$

$\bar{D}_o^{t+1}(x^t, y^t, b^t; 1, 1) > 0$ and $\bar{D}_o^t(x^{t+1}, y^{t+1}, b^{t+1}; 1, 1) < 0$, so $LTECHCH > 0$ indicates technical progress.

To compute the Malmquist-Luenberger productivity index in (3.17) and Luenberger productivity index in (3.20), including their decomposed components in (3.18), (3.19), (3.21) and (3.22), four distance functions must be estimated, i.e., $D_o^t(x^t, y^t, b^t; y^t, -b^t)$, $D_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})$, $D_o^t(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, b^{t+1})$ and $D_o^{t+1}(x^t, y^t, b^t; y^t, -b^t)$. The latter two are mixed-period distance functions which are obtained by evaluating performance of an airport from one period in another period. Färe, Grosskopf, Norris, and Zhang (1994) make use of the fact that the output distance function is reciprocal to the output-based Farrell measure of technical efficiency, and then modify the directional output distance function $\vec{D}_o(x, y, b; y, -b)$ in (3.7) to accommodate time period. The computation steps are summarized below.

1) To estimate $D_o^t(x_{k'}^t, y_{k'}^t, b_{k'}^t; y_{k'}^t, -b_{k'}^t)$ for airport k' , compare $(y_{k'}^t, b_{k'}^t)$ to the frontier at time t , and solve the following linear program:

$$\begin{aligned}
 D_o^t(x_{k'}^t, y_{k'}^t, b_{k'}^t; y_{k'}^t, -b_{k'}^t) &= \max \beta \\
 \text{s.t.} & \\
 \sum_{k \in K} \lambda_k^t y_{km}^t &\geq (1 + \beta) y_{k'm}^t, m = 1, \dots, M, \\
 \sum_{k \in K} \lambda_k^t b_{kj}^t &= (1 - \beta) b_{k'j}^t, j = 1, \dots, J, \\
 \sum_{k \in K} \lambda_k^t x_{kn}^t &\leq x_{k'n}^t, n = 1, \dots, N, \\
 \lambda_k^t &\geq 0, k = 1, \dots, K
 \end{aligned} \tag{3.23}$$

2) To estimate $D_o^{t+1}(x_{k'}^{t+1}, y_{k'}^{t+1}, b_{k'}^{t+1}; y_{k'}^{t+1}, -b_{k'}^{t+1})$ for airport k' , compare $(y_{k'}^t, b_{k'}^t)$ to the frontier at time $t + 1$, and solve the following linear program:

$$\begin{aligned}
 D_o^{t+1}(x_{k'}^{t+1}, y_{k'}^{t+1}, b_{k'}^{t+1}; y_{k'}^{t+1}, -b_{k'}^{t+1}) &= \max \beta \\
 \text{s.t.} \\
 \sum_{k \in K} \lambda_k^{t+1} y_{km}^{t+1} &\geq (1 + \beta) y_{k'm}^{t+1}, m = 1, \dots, M, \\
 \sum_{k \in K} \lambda_k^{t+1} b_{kj}^{t+1} &= (1 - \beta) b_{k'j}^{t+1}, j = 1, \dots, J, \\
 \sum_{k \in K} \lambda_k^{t+1} x_{kn}^{t+1} &\leq x_{k'n}^{t+1}, n = 1, \dots, N, \\
 \lambda_k^{t+1} &\geq 0, k = 1, \dots, K
 \end{aligned} \tag{3.24}$$

3) To estimate $D_o^t(x_{k'}^{t+1}, y_{k'}^{t+1}, b_{k'}^{t+1}; y_{k'}^{t+1}, -b_{k'}^{t+1})$ for airport k' , compare $(y_{k'}^{t+1}, b_{k'}^{t+1})$ to the frontier at time t , and solve the following linear program:

$$\begin{aligned}
 D_o^t(x_{k'}^{t+1}, y_{k'}^{t+1}, b_{k'}^{t+1}; y_{k'}^{t+1}, -b_{k'}^{t+1}) &= \max \beta \\
 \text{s.t.} \\
 \sum_{k \in K} \lambda_k^t y_{km}^t &\geq (1 + \beta) y_{k'm}^{t+1}, m = 1, \dots, M, \\
 \sum_{k \in K} \lambda_k^t b_{kj}^t &= (1 - \beta) b_{k'j}^{t+1}, j = 1, \dots, J, \\
 \sum_{k \in K} \lambda_k^t x_{kn}^t &\leq x_{k'n}^{t+1}, n = 1, \dots, N, \\
 \lambda_k^t &\geq 0, k = 1, \dots, K
 \end{aligned} \tag{3.25}$$

4) To estimate $D_o^{t+1}(x_{k'}^t, y_{k'}^t, b_{k'}^t; y_{k'}^t, -b_{k'}^t)$ for airport k' , compare $(y_{k'}^t, b_{k'}^t)$ to the frontier at time $t + 1$, and solve the following linear program:

$$\begin{aligned}
 &D_o^{t+1}(x_{k'}^t, y_{k'}^t, b_{k'}^t; y_{k'}^t, -b_{k'}^t) = \max \beta \\
 &s.t. \\
 &\sum_{k \in K} \lambda_k^{t+1} y_{km}^{t+1} \geq (1 + \beta) y_{k'm}^t, m = 1, \dots, M, \\
 &\sum_{k \in K} \lambda_k^{t+1} b_{kj}^{t+1} = (1 - \beta) b_{k'j}^t, j = 1, \dots, J, \\
 &\sum_{k \in K} \lambda_k^{t+1} x_{kn}^{t+1} \leq x_{k'n}^t, n = 1, \dots, N, \\
 &\lambda_k^{t+1} \geq 0, k = 1, \dots, K
 \end{aligned} \tag{3.26}$$

Substituting (3.23) – (3.26) for the corresponding terms in (3.17) – (3.19), the Malmquist-Luenberger productivity index and the two components can be obtained. Similarly, substituting (3.23) – (3.26) for the corresponding terms in (3.20) – (3.22), the Luenberger productivity index and the two components can be obtained.

In summary, the Malmquist-Luenberger and Luenberger productivity indexes together with their components provide more insightful information regarding sources of productivity change between two time periods. Chapter 4 will describe the first case study which is summarized from three publications (Pathomsiri and Haghani, 2004; Pathomsiri, Haghani and Schonfeld, 2005; Pathomsiri, Haghani, Dresner and Windle, 2006a). The study is the first attempt to assess productivity of airports operating in multiple airport systems using the DEA model. This case study provides primary understanding on typical results when undesirable outputs are not ignored. Then another case study of U.S. airports will address the shortcomings later.

CHAPTER 4

CASE STUDY 1

PRODUCTIVITY OF AIRPORTS IN MULTIPLE AIRPORT SYSTEMS

Many metropolitan regions around the world are served by multiple commercial airports. These regions are called “multiple airport systems” or MASs among aviation community. There have been many stories about functional failures in planning and managing of MASs worldwide due to over-investment or underutilization (Caves and Gosling, 1999; de Neufville, 1995; de Neufville and Odoni, 2003). It is well-documented that several airports in MAS cannot achieve sufficient traffic to economically justify capital investment. In other words, the investment is actually not sufficiently productive. However, it is very surprising that there is no productivity study that focuses on airports in multiple airport systems, though MASs involve several times more capital investment. If one is about to assess two airports comparable in both size and market, an airport in single-airport system which is enjoying its monopolistic status perhaps performs no less efficiently than an airport that is struggling with competitors in an MAS. In a productivity study of mixed samples of airports operating in single-airport and multiple-airport systems, it was found that U.S. airports in MASs were not operating more efficiently than other U.S. airports (Sarkis, 2000).

This case study aims to fill this gap by looking at the productivity of airports in MASs. The results may be perceived as like-a-like comparisons among airports operating

in the same market structure. Due to the unavailability of data on undesirable outputs at international airports, the study is therefore restricted to the consideration of desirable outputs only. As a result, Data Envelopment Analysis model is applicable. This chapter describes the definition of MAS, modeling of airport operation, input and output measures of airport operations and data collection. Note that the content in this chapter is based on three publications, i.e., Pathomsiri and Haghani (2004), Pathomsiri, Haghani and Schonfeld (2005) and Pathomsiri, Haghani, Dresner and Windle (2006a).

4.1 Definition of multiple airport system

Multiple airport system (MAS) is explicitly defined in few publications (de Neufville, 1995; de Neufville and Odoni, 2003; Hansen and Weidner, 1995). In one textbook (de Neufville and Odoni, 2003), the authors defined an MAS as “the set of significant airports that serve commercial transport in a metropolitan region, without regard to ownership or political control of the individual airports.” This definition involves four important points. First, MAS focuses on airports serving commercial transport. Second, MAS refers to a metropolitan region rather than a city. The region can expand to cover several cities as in the case of New York/New Jersey. Third, MAS focuses on the market, not the ownership of the airports. Although five airports in London area are owned by three different organizations, they form the London MAS since they all serve the same market. Finally, MAS focuses on significant airports. The authors suggest a threshold of more than one million passengers per year for identifying significant airports.

Another paper (Hansen and Weidner, 1995) defined an MAS as two or more airports operating with scheduled passengers enplanements in a contiguous metropolitan

area in such a way as to form an integrated airport system and satisfies both of the following criteria:

- Each airport in the system is included in the same community by the Federal Aviation Administration (FAA) or within 50 km. (30 miles) of the primary airport of an FAA-designated “large-hub” community, or each airport is in the same Metropolitan Statistical Area (MSA) or Consolidated MSA (CMSA).

- The Herfindahl Concentration Index (HCI) for the airports is less than 0.95.

HCI is the sum of squared market shares of all airports in an MAS. For example, in 2003, distribution pattern of passenger traffic in Baltimore/Washington MAS was 20,094,756 (39.34%), 16,767,767 (32.83%) and 14,214,803 (27.83%) at Baltimore/Washington International (BWI), Washington Dulles International (IAD) and Ronald Reagan Washington National (DCA) respectively. Therefore, HCI is equal to $0.3934^2 + 0.3283^2 + 0.2783^2 = 0.34$. Similarly, in Houston MAS, in 2002 George Bush Intercontinental (IAH), William P. Hobby (HOU) and Ellington Field (EFD) accommodated 33,905,253 (80.69%), 8,035,727 (19.112%) and 76,035 (0.18%) passengers respectively. HCI is equal to $80.69^2 + 19.12^2 + 0.18^2 = 0.688$. By the above criteria, the Houston MAS is not so concentrated but somehow competitive. Note that for a single airport system, HCI is 1.0. For an MAS where traffic is evenly divided among N airports, HCI is $1/N$ (Baltimore/Washington MAS may be a close example).

The above two examples of MAS definitions indeed are very similar. The difference may be the significance of the airport. One uses a threshold of passenger traffic to identify the MAS whereas the other uses HCI, regardless of traffic volume. It is

harmless to think of the latter criterion as a measure of sufficient significance in a sense that only competitive MASs are included in the analysis.

Since definitions are in good agreement and well-documented in the publications, 14 MASs in the U.S. from (Hansen and Weidner, 1995) are then adopted. For more comprehensive study, the scope is expanded to other MASs worldwide. In this study, the lists of MASs in publications (Caves and Gosling, 1999; de Neufville, 1995; de Neufville and Odoni, 2003) were collected and checked if they satisfy both definitions. Eventually, we identified another 11 non-US MASs. Totally, there are 25 MASs in this study, involving 75 airports in four continents, i.e., North America, South America, Europe and Asia. Table 4.1 provides the list of all 25 MASs together with the airports in the systems along with the International Civil Aviation Organization (ICAO) airport codes. The Table shows two computed HCIs, one based on passenger and the other based on aircraft movements. This means that airports in the same region may compete for passengers or aircraft movements or both. As a result, as long as either HCI is below 0.95, the region is an MAS.

Table 4.1 List of multiple airport systems and corresponding Herfindahl Concentration Indices, 2002

	Region	Airport Code	Airport Name	Aircraft Movements	HCI-Air	Total Passengers	HCI-PAX
1	Chicago, IL, USA	ORD	O'Hare International	922,817	0.596	66,565,952	0.670
		MDW	Midway International	304,304		17,371,036	
		CGX	Merrill C. Meigs	31,972		86,483	
2	New York City, NY, USA	EWR	Newark Liberty International, NJ	405,562	0.191	29,202,654	0.315
		JFK	John F. Kennedy International, NY	287,606		29,943,084	
		LGA	LaGuardia, NY	362,439		21,986,679	
		ISP	Long Island MacArthur, NY	223,063		1,890,580	
		HPN	Westchester County, NY	167,776		930,097	
		SWF	Stewart International, NY	123,642		362,017	
3	Los Angeles, CA, USA	LAX	Los Angeles International, CA	645,424	0.209	56,223,843	0.543
		SNA	John Wayne, CA	368,627		7,903,066	
		ONT	Ontario International, CA	149,292		6,517,050	
		BUR	Bob Hope, CA	162,211		4,620,683	
		PSP	Palm Spring International, CA	85,243		1,108,695	
		LGB	Long Beach, CA	350,603		1,453,412	
		OXR	Oxnard, CA	88,027		45,306	
		PMD	Palmdale Regional, CA	33,352		226	
4	San Francisco, CA, USA	SFO	San Francisco International, CA	351,453	0.240	31,456,422	0.415
		SJC	Mineta San Jose International, CA	207,510		11,115,778	
		OAK	Oakland International, CA	371,988		13,005,642	
		STS	Sonoma County, CA	114,854		3,598	
		CCR	Buchanan Field, CA	142,329		0	
5	Santa Barbara, CA, USA	SBA	Santa Barbara, CA	159,835	0.562	728,307	0.863
		SMX	Santa Maria Public, CA	76,426		58,104	
6	Dallas/Fort Worth, TX, USA	DFW	Dallas/Fort Worth International, TX	765,109	0.632	52,828,573	0.826
		DAL	Dallas Love Field, TX	245,564		5,622,754	
7	Houston, TX, USA	IAH	George Bush Intercontinental, TX	456,831	0.432	33,905,253	0.688
		HOU	William P. Hobby, TX	246,230		8,035,727	
		EFD	Ellington Field, TX	102,016		76,035	
8	Washington, DC, USA	BWI	Baltimore/Washington International, MD	304,921	0.349	19,012,529	0.342
		IAD	Washington Dulles International, VA	372,636		17,075,965	
		DCA	Ronald Reagan Washington National, DC	215,691		12,871,885	
9	Miami, FL, USA	MIA	Miami International, FL	446,235	0.383	30,060,241	0.443
		FLL	Fort Lauderdale - Hollywood International, FL	280,737		17,037,261	
		PBI	Palm Beach International, FL	166,908		5,483,662	
10	Pensacola, FL, USA	PNS	Pensacola Regional, FL	130,826	0.501	1,345,970	0.565
		VPS	Okaloosa Regional, FL	118,423		631,592	

Table 4.1 List of multiple airport systems and corresponding Herfindahl Concentration Indices, 2002 (Continued)

	Region	Airport Code	Airport Name	Aircraft Movements	HCI-Air	Total Passengers	HCI-PAX	
11	Detroit, MI, USA	DTW	Detroit Metropolitan Wayne County, MI	490,885	0.784	32,477,694	1.000	
		DET	Detroit City, MI	69,066				0
12	Cleveland, OH, USA	CLE	Cleveland Hopkins International, OH	251,758	0.563	10,455,204	0.855	
		CAK	Arkon-Canton, OH	119,958				894,798
13	Norfolk, VA, USA	ORF	Norfolk International, VA	125,622	0.542	3,464,246	0.775	
		PHF	Newport News/Williamsburg International, VA	228,504				515,056
14	Oshkosh/Appleton, WI, USA	ATW	Outagamie County Regional, WI	57,755	0.555	491,744	0.984	
		OSH	Wittman Regional, WI	115,288				3,912
15	Montreal, Canada	YUL	Montreal-Dorval International	192,225	0.750	7,816,052	0.800	
		YMX	Montreal-Mirabel International	32,977				990,937
16	Rio de Janeiro, Brazil	GIG	Rio De Janeiro-Galeao International	83,731	0.514	5,810,868	0.500	
		SDU	Santos Dumont	117,144				5,626,328
17	Sao Paulo, Brazil	GRU	Sao Paulo Guarulhos International	160,451	0.531	12,804,091	0.500	
		CGH	Congonhas	266,231				12,562,319
18	Buenos Aires, Argentina	AEP	Aeroparque Jorge Newbery	91,350	0.316	4,519,424	0.497	
		EZE	Ezeiza International	50,755				4,054,473
		DOT	International Don Torcuato	23,392				23,148
		SFD	San Fernando	34,819				11,676
19	London, United Kingdom	LHR	London Heathrow	466,554	0.305	63,338,641	0.379	
		LTN	London Luton	80,921				6,496,258
		LGW	London Gatwick	242,380				29,628,423
		STN	London Stansted	170,774				16,049,288
		LCY	London City	56,102				1,604,773
20	Glasgow, United Kingdom	GLA	Glasgow	105,197	0.378	7,807,060	0.422	
		EDI	Edinburgh	118,419				6,932,106
		PIK	Glasgow Prestwick International	43,346				1,487,113
21	Paris, France	CDG	Roissy-Charles-de Gaulle	510,098	0.586	48,350,172	0.562	
		ORY	Orly	211,080				23,169,725
22	Berlin, Germany	TXL	Tegel	127,470	0.440	9,879,888	0.680	
		SXF	Schoenefeld	37,389				1,688,028
		THF	Tempelhof	48,026				612,867
23	Milan, Italy	LIN	Linate	110,494	0.551	7,815,316	0.573	
		MLP	Malpensa	214,886				17,441,250
24	Moscow, Russia	SVO	Sheremetyevo	124,630	0.357	10,895,225	0.404	
		VKO	Vnukovo	65,759				3,120,210
		DME	Domodedovo	84,102				6,683,268
25	Tokyo, Japan	HND	Tokyo International (Haneda)	282,674	0.535	61,079,478	0.564	
		NRT	New Tokyo International (Narita)	164,270				28,883,606

4.2 Modeling airport operations

Each airport in the MAS is viewed as a production unit. As a result, airport operation can be modeled as a production process that requires some inputs for running day-to-day operations in order to produce some target outputs. Necessary inputs include production factors such as capital and labor. Most airport managers set target to maximize movement of aircrafts, passenger throughput and quantity of cargo transported. These outputs are highly desirable and the primary reason for building an airport. Due to the unavailability of data on undesirable outputs (e.g., delays, noise) at international airports, the assessment has to be restricted to the consideration of desirable outputs only. As a result, Data Envelopment Analysis (DEA) is applicable as an analytical tool.

4.3 Input and output measures of airport operations

The formulation of any DEA model given in Table 2.5 requires data on quantity of inputs and desirable outputs, (x_{km}, y_{km}) for individual airports. The selection of inputs and outputs is an important decision issue in the assessment of airport productivity. The general suggestion is to include all important measures that are in the interest of the management. Such measures should be common for all airports so that the performance would provide meaningful interpretation. In practice, the main problem is the availability of the data across all airports rather than model limitations. After all, three common physical inputs are considered in this analysis:

x_1 = Land area (LAND), acre

x_2 = Number of runways (RW)

x_3 = Runway area (RWA), acre

These inputs are necessary infrastructure for all airports. Land area (acre) represents a considerable share of capital investment that an airport should fully utilize. Number of runways counts all existing runways at the airport, regardless of their utilization level. Runway area is the summation of product between length and width of all runways. The consideration of runway area should explain variations in productivity better than using the number of runway alone, since it takes into account the effect of size and design configuration such as length, width, and separation. Other inputs such as terminal area, number of gates, number of employees and expense cannot be included due to the lack of complete data across samples.

For the set of desirable outputs, it is assumed that airport managers aim at producing the following two outputs as much as possible:

$$y_1 = \text{Aircraft movements}$$

$$y_2 = \text{Passengers}$$

Number of aircraft movements includes all kinds of movements, i.e., commercial aircrafts, cargo aircrafts, general aviation, and others. The number of passengers counts both arriving and departing passengers for all type of commercial passengers, i.e., international, domestic and direct transit passengers. Other desirable outputs such as cargo throughput and revenues cannot be considered due to the lack of complete data across all samples, especially for small U.S. and non-U.S. airports. Inclusion of these outputs will reduce sample size drastically; hence, it is decided to maintain all samples. Note that these input and output measures may be rather limited to partial factors of airport operations, but they have been used in previous studies such as Gillen and Lall (1997, 1998); Pels, Nijkamp and Rietveld

(2001,2003) (see Table 2.4 for details). Given the above-selected three inputs and three desirable outputs, the assessment may be perceived as the measurement of productive efficiency of airside operation.

4.4 Data collection

The study period is during 2000 – 2002. On the output side, statistics on the number of passengers and aircraft movements are collected from Airports Council International publications (ACI, 2002 - 2004). The missing data are supplemented from several sources such as FAA website (FAA, 2004a), airports' official websites, airport newsletters, reports, airport contacts and e-mail correspondences.

Collecting input data caused more trouble since there is no single source available at hand. Airport Master Record (AMS) database (FAA, 2004b) contains the most recent data on characteristics of US airports. The best effort was made to verify this recent data with airport managers whether there are runway expansions or constructions during the period 2000 – 2002. Some airports had improved their runways. For example, George Bush Intercontinental (IAH) expanded and extended runway 15R/33L to 10000' x 150' in 2002. Detroit Metropolitan Wayne County (DTW) opened its 6th runway on December 11, 2001. The number of runways is edited accordingly. The number of runway and runway acreage are computed precisely by the time it is in service during the year, rounding down in month. In case of DTW, for example, it is concluded that it had 5 and 6 runways in 2001 and 2002, respectively.

Input data of non-US airports are more difficult to collect since there is no database such as AMS (FAA, 2004b). Inevitably, one has to rely on information from airports' official websites, airport newsletters, reports, airport contacts and e-mail correspondences. Also, it is

verified with airport managers whether there was any change in runway configuration during 2000 – 2002. Similarly to the US airport case, it is found that Narita International (NRT) opened its new second parallel runway in April 2002. As a result, it used 1.667 (= 1 + 8/12) runways in 2002.

Ultimately, the study had to drop Santos Dumont/Rio de Janeiro (SDU), International Don Torcuato/Buenos Aires (DOT) and Vnukovo/Moscow (VKO) airports from the sample due to unavailable land area data. The final dataset used in this study contains 72 airports with complete input and output data. The sample size is relatively larger than most previous studies (Abbott and Wu, 2002; Adler and Berechman, 2001; Bazargan and Vasigh, 2003; Fernandes and Pacheco, 2001, 2002, 2005; Gillen and Lall, 1997, 1998; Hooper and Hensher, 1997; Martin and Roman, 2001; Martin-Cejas (2002); Murillo-Melchor, 1999; Nyshadham and Rao, 2000; Oum, Yu and Fu, 2003; Pacheco and Fernandes 2003; Parker, 1999; Pels, Nijkamp and Rietveld, 2001, 2003; Salazar de la Cruz, 1999; Sarkis, 2000; Sarkis and Tulluri, 2004; Yoshida, 2004; Yu, 2004).

The number of samples was checked against several applicable rules of thumb to guarantee the sufficiency and meaningful interpretation. In DEA applications, one frequent problem is a lack of discriminatory power between DMUs as a result of an excessive number of measures with respect to the total number of DMUs. The larger the number of input and output measures for a given number of airports the less discriminatory the DEA model becomes. Given a certain set of samples, this means that the addition of measures will reduce the discriminatory power of the DEA model. Essentially, this is because it is possible that an airport may dominate all others on one measure, which in turn makes it look equally efficient compared to other efficient airports. This is a major issue encountered by Parker (1999),

Adler and Berechman (2001) and Yu (2004). To avoid this problem, the straightforward way is to guarantee that there will be a sufficient number of airports for comparison, regarding any of the measures.

Boussofiene, Dyson and Thanassoulis (1991) recommend that the total number of DMUs be much greater than the number of inputs times the number of outputs. Compared to this analysis where three inputs and two outputs are selected for the assessment of airport productivity; the number of samples needs to be much more than 3×2 or 6 airports in order to reduce the chance that an airport is too dominant compared to the others on a particular measure. According to the recommendation, the sample size of 72 airports is deemed satisfactory.

To avoid losing discriminatory power, Cooper, Seiford and Tone (2000: page 103) recommend that the desired number of DMUs exceed $m + s$ several times. They suggest a more stringent rule of thumb in the following formula (Cooper, Seiford and Tone, 2000: page 252).

$$n \geq \max\{m \times s, 3(m + s)\} \quad (4.1)$$

where n is the number of DMUs, m and s are the numbers of input and output measures respectively.

Substituting m and s , yields the minimum number of samples:

$$n \geq \max\{3 \times 2, 3(3 + 2)\} = \max\{6, 15\} = 15 \quad (4.2)$$

Again, the sample size of 72 satisfies this recommendation. After all, it can be concluded that the sample size is sufficient for the analysis. Table 4.2 summarizes the descriptive statistics of the samples. Input measures are rather stable over time; only slight

changes in number of runways and runway acreage are recorded. The variation in terms of the range between maximum and minimum is wide, indicating that airports in MAS are much different in scale of operation. Similarly, airports' outputs are widely variable indicating that airports are much different in scope of operation. Six partial productivity ratios are also shown to provide more information on the utilization of airport.

In the next chapter, results from assessing productivity of 72 airports by DEA model will be presented. The assessment will be discussed with respect to operational efficiency of individual airports. In addition, Censored Tobit regression models are also estimated for explaining variations in total productivity level.

Table 4.2 Descriptive statistics of 72 airports in MASs, 2000 - 2002

Variables	Statistics	2000	2001	2002
Land acreage area (LAND)	Min	70	70	70
	Max	18,076	18,076	18,076
	Mean	2,865	2,865	2,865
	S.D.	3,419	3,419	3,419
Number of runways (RW)	Min	1	1	1
	Max	7	7	7
	Mean	2.69	2.69	2.72
	S.D.	1.26	1.26	1.28
Runway acreage area (RWA)	Min	9.78	9.78	9.78
	Max	295.54	295.54	298.60
	Mean	79.56	79.66	80.98
	S.D.	52.84	52.81	54.41
Annual aircraft operations (AIR)	Min	30,479	31,240	31,972
	Max	908,989	911,917	922,817
	Mean	234,800	223,829	216,093
	S.D.	188,593	179,799	172,890
Annual total passengers (PAX)	Min	0	0	0
	Max	72,144,244	67,448,064	66,565,952
	Mean	14,063,577	13,363,106	13,240,016
	S.D.	18,120,258	16,989,050	16,786,913
PAX/LAND	Min	0	0	0
	Max	37,316	32,254	32,333
	Mean	6,561	6,379	6,436
	S.D.	7,678	7,449	7,662
AIR/LAND	Min	2	2	2
	Max	774	757	736
	Mean	173	163	157
	S.D.	174	162	156
AIR/RW	Min	19,957	18,088	16,489
	Max	195,858	189,452	184,314
	Mean	83,260	79,783	76,211
	S.D.	45,021	43,090	40,772
AIR/RWA	Min	362	328	299
	Max	15,765	15,401	14,983
	Mean	3,332	3,166	3,021
	S.D.	2,257	2,135	2,052
PAX/RW	Min	0	0	0
	Max	27,389,915	25,379,370	21,112,880
	Mean	4,861,631	4,657,794	4,502,157
	S.D.	5,665,696	5,379,152	5,049,647
PAX/RWA	Min	0	0	0
	Max	583,604	548,702	572,148
	Mean	151,358	145,135	142,365
	S.D.	148,524	141,262	141,131

CHAPTER 5

CASE STUDY 1

RESULTS AND DISCUSSION

5.1 Selection of a DEA model

Similar to Martin and Roman (2001), it is assumed that once an airport has invested in the infrastructure, it is difficult for managers to disinvest to save costs. Consequently, airport managers are more interested to know the probable levels of outputs, given the existing infrastructure (Fernandes and Pacheco, 2002). From this viewpoint, the output-orientation DEA model is preferred. Since the analysis is focused on rather narrow study period during 2000 – 2002, the variable return to scale (VRS) frontier type is chosen to reflect the short-term view (Ganley and Cubbin, 1992). In VRS frontier type DMUs are not penalized for operating at a non-optimal scale (Banker, 1984; Banker and Thrall, 1992). After all, the applicable model is the DEA-Output-VRS. Its mathematical formulation is given below:

$$\begin{aligned}
 & \max \Phi \\
 & s.t. \\
 & \sum_{k \in K} \lambda_k y_{km} - s_m^+ = \Phi y_{km}, m = 1, \dots, M, \\
 & \sum_{k \in K} \lambda_k x_{kn} + s_n^- = x_{kn}, n = 1, \dots, N, \\
 & \sum_{k \in K} \lambda_k = 1, k = 1, \dots, K \\
 & \lambda_k \geq 0
 \end{aligned} \tag{5.1}$$

For each year during 2000 – 2002, the DEA model in (5.1) is solved 72 times; i.e., one time for each airport, to determine the optimal efficiency scores Φ^* . Φ^* measures the

level of inefficiency. An efficient airport will have $\Phi^* = 1$ which means it does not need to increase its outputs. It is already on the efficient production frontier. In other words, the airport is more productive than others, given the same amount of inputs. All inefficient airports will have $\Phi^* > 1$. The higher value of Φ^* shows greater inefficiencies.

5.2 Efficient scores

Table 5.1 presents the efficiency scores of 72 airports during 2000 – 2002. Bold typeface highlights airports on efficient production frontier. For example, in 2002, there are 12 efficient airports i.e. O'Hare International (ORD), Merrill C. Meigs (CGX)¹, LaGuardia (LGA), Los Angeles International (LAX), John Wayne (SNA), Oxnard (OXR), Palmdale (PMD), Congonhas/Sao Paulo (CGH), Heathrow/London (LHR), Stansted/London (STN), City/London (LCY), and Haneda/Tokyo (HND). These 12 airports form a piece-wise linear efficient production frontier under variable return-to-scale assumption.

Seemingly, efficient airports can be classified into two groups i.e., the busy and the compact. The busy group is usually a primary or major airport in the region such as O'Hare International (ORD), Los Angeles International (LAX), Aeroparque Jorge Newbery/Buenos Aires (AEP), Heathrow/London (LHR), Haneda/Tokyo (HND) and Narita/Tokyo (NRT). Their land areas are relatively large, ranging from 2,000 – 8,000 acres. Annual passenger traffics are consistently among the top of the world. Another interesting observation is that they dominate the market by having more than 50% of passengers. Their high traffic flows enable airports to operate more efficiently at higher utilization level than others.

The compact group includes Merrill C. Meigs (CGX), LaGuardia (LGA), John Wayne (SNA), Oxnard (OXR), Palmdale (PMD), Congonhas/Sao Paulo (CGH),

¹ The airport was permanently closed in March 2003.

Stansted/London (STN) and City/London (LCY). These airports are relatively small in size (between 70 – 960 acres) with one or two runways. They are alternative airports, except Congonhas/Sao Paulo (CGH) which is a primary airport constrained in downtown area. Although traffic may not be so high, they still can be efficient airports because of their sufficiently high utilization rate.

Airports with efficiency scores below two may be considered satisfactorily efficient in terms of input utilization. The airports with scores consistently higher than two should be monitored closely for improving efficiency. Some airports with consistently very high scores such as Montreal-Mirabel (YMX), Glasgow Prestwick International (GLA), Schoenefeld/Berlin (SXF), and Tempelhof/Berlin (THF) are significantly under-utilized or over-invested. These airports tend to use comparable inputs to others but service far fewer aircraft movements and passengers.

Table 5.1 Efficiency scores, 2000 – 2002

No.	Multiple Airport System	Airport Code	2000	2001	2002
1	Chicago, IL, USA	ORD	1.000	1.000	1.000
		MDW	1.302	1.293	1.174
		CGX	1.000	1.000	1.000
2	New York City, NY, USA	EWR	1.251	1.251	1.234
		JFK	2.041	2.119	2.076
		LGA	1.000	1.000	1.000
		ISP	2.166	2.058	1.996
		HPN	2.067	2.049	2.197
		SWF	2.842	3.330	2.981
3	Los Angeles, CA, USA	LAX	1.000	1.000	1.000
		SNA	1.000	1.000	1.000
		ONT	2.479	2.399	2.446
		BUR	2.407	2.354	2.266
		PSP	4.670	4.510	4.324
		LGB	1.259	1.285	1.231
		OXR	1.000	1.000	1.000
		PMD	1.000	1.000	1.000
4	San Francisco, CA, USA	SFO	1.640	1.786	1.816
		SJC	1.596	1.691	1.977
		OAK	1.230	1.335	1.398
		STS	2.828	2.730	3.210
		CCR	1.773	2.404	2.558
5	Santa Barbara, CA, USA	SBA	2.547	2.578	2.527
		SMX	5.198	4.982	4.823
6	Dallas/Fort Worth, TX, USA	DFW	1.085	1.164	1.206
		DAL	1.931	1.956	1.809
7	Houston, TX, USA	IAH	1.396	1.352	1.375
		HOU	1.951	1.916	1.806
		EFD	5.813	6.240	4.710
8	Washington, DC, USA	BWI	2.050	1.902	1.940
		IAD	1.283	1.407	1.361
		DCA	1.414	1.637	1.779
9	Miami, FL, USA	MIA	1.132	1.180	1.134
		FLL	1.720	1.615	1.552
		PBI	2.490	2.460	2.732
10	Pensacola, FL, USA	PNS	3.293	3.252	2.818
		VPS	3.285	3.203	3.113
11	Detroit, MI, USA	DTW	1.486	1.525	1.692
		DET	1.214	1.846	2.664
12	Cleveland, OH, USA	CLE	1.739	1.888	1.990
		CAK	4.117	3.953	4.014

Table 5.1 Efficiency scores, 2000 – 2002 (Continued)

No.	Multiple Airport System	Airport Code	2000	2001	2002
13	Norfolk, VA, USA	ORF	3.107	3.161	2.927
		PHF	1.844	1.734	1.613
14	Oshkosh/Appleton, WI, USA	ATW	5.871	6.642	6.383
		OSH	4.478	4.596	3.894
15	Montreal, Canada	YUL	2.792	2.846	2.638
		YMX	9.679	10.306	11.137
16	Rio de Janeiro, Brazil	GIG	4.592	4.021	4.249
17	Sao Paulo, Brazil	GRU	2.016	1.976	2.170
		CGH	1.082	1.000	1.000
18	Buenos Aires, Argentina	AEP	1.000	1.000	1.260
		EZE	5.630	5.910	6.858
		SFD	2.810	2.681	2.455
19	London, United Kingdom	LHR	1.000	1.000	1.000
		LTN	1.191	1.275	1.490
		LGW	1.113	1.080	1.199
		STN	1.000	1.000	1.000
		LCY	1.000	1.000	1.000
20	Glasgow, United Kingdom	GLA	2.899	2.402	2.270
		EDI	3.756	3.272	3.063
		PIK	8.583	8.300	8.457
21	Paris, France	CDG	1.395	1.290	1.221
		ORY	2.192	2.304	2.286
22	Berlin, Germany	TXL	2.798	2.687	2.744
		SXF	8.022	9.144	9.759
		THF	7.784	7.744	7.676
23	Milan, Italy	LIN	3.260	2.458	2.367
		MLX	1.480	1.520	1.615
24	Moscow, Russia	SVO	2.887	2.676	2.750
		DME	8.025	5.809	4.142
25	Tokyo, Japan	HND	1.070	1.000	1.000
		NRT	1.000	1.000	1.101

Note: Bold typeface highlights efficient airports.

5.3 Determination of airport productivity

It may not be sufficient to just describe efficiency score based on historical data. For planning an airport, the understanding of factors affecting efficiency score is even more useful. In this case study, causal models for explaining the variations in efficiency score are estimated so that an airport manager can predict future productivity based on given information. In particular, this information is treated as usual exploratory variables. The information may include number of runways, land area, number of gates, noise strategies, proportion of General Aviation (GA) traffic, proportion of international passengers, type of ownership/management, etc. The dependent variable is the efficiency score that indicates the total productivity level of an airport.

By the nature of the DEA-Output-VRS model, the value of efficiency scores can only be in the range of 1 to infinity. Because of this special type of limited dependent variable, simple regression is not an appropriate model. Its underlying assumptions are violated, causing inconsistency in estimated coefficients. The Censored Tobit regression model (Tobin, 1958; Maddala, 1983; Amemiya, 1984; Gillen and Lall, 1997; Greene, 2002; Greene, 2003) is more appropriate. In this case, efficiency score of airport y_i is represented by Equation (5.2).

$$y_i = \begin{cases} \beta x_i + \varepsilon_i & \text{if } y_i > 1 \\ 1 & \text{if } y_i \leq 1 \end{cases} \quad (5.2)$$

y_i is an efficiency score that is observable for values greater than 1 and is censored for values less than or equal to 1. Efficiency scores of all efficient airports are

censored at 1, regardless of values of independent variables x_i . β and ε_i are the coefficients and the error term of the Tobit model respectively. The coefficients β can be estimated with the Maximum Likelihood (ML) method. ML estimation for the Tobit model involves dividing the observations into two sets. The first set contains uncensored observations. The second set contains censored observations. For $y_i > 1$, assuming $y_i \sim N(\mu, \sigma^2)$, then the log-likelihood function is written as shown in Equation (5.3).

$$\ln L = \sum_{Uncensored} \ln \frac{1}{\sigma} \phi \left(\frac{y_i - \beta x_i}{\sigma} \right) + \sum_{Censored} \ln \Phi \left(\frac{1 - \beta x_i}{\sigma} \right) \quad (5.3)$$

where ϕ and Φ are the respective probability and cumulative density functions. Unlike simple regression models, the estimated coefficients cannot be interpreted as marginal effects. Equation (5.4) is used to compute marginal effect of variable k (Gillen and Lall, 1997).

$$\frac{\partial E(y | x)}{\partial x_k} = \text{Prob}(\text{Uncensored} | x) \beta_k = \Phi \left(\frac{\beta x - 1}{\sigma} \right) \beta_k \quad (5.4)$$

Goodness-of-fit may be measured by using R^2_{ANOVA} , computed by Equation (5.5).

This fit measure takes the variance of the estimated conditional mean divided by the variance of the observed variable (Greene, 2002).

$$R^2_{ANOVA} = \frac{\frac{1}{n} \sum_{i=1}^n \left(y'_i - \bar{y}' \right)^2}{\frac{1}{n} \sum_{i=1}^n \left(y_i - \bar{y} \right)^2} = \frac{\text{Var}(\text{Predicted conditional mean})}{\text{Var}(\text{Dependent variable})} \quad (5.5)$$

Some econometric packages can be used to estimate Censored Tobit Regression model such as EViews (QMS, 2005), LIMDEP (Greene, 2002), and STATA (StataCorp, 2005). In this case study, LIMDEP version 8.0 (Greene, 2002) is used.

5.4 Factors affecting productive efficiency of airports in MASs

The Tobit model has efficiency score Φ as the dependent variable. Related literature suggests many possible exploratory variables qualify as independent variables (Gillen and Lall, 1997). In this case study, five groups of independent variables are investigated. The proxy of each group entering the model is essentially based on data availability.

First, *Airport characteristics* are represented here by physical characteristics, basically input measures that are used in the DEA model, i.e., land area (LAND), number of runway (RW) and runway area (RWA). These inputs certainly play a major role in accommodating traffic. However, one should be aware that having more of these inputs does not necessarily mean more outputs.

Second, *Airport services* are mainly represented by outputs of airport operations which consist of number of aircraft movements (AIR) and passengers (PAX). One would expect that more services contribute to higher efficiency. However, this is not necessarily true since efficiency takes into account both inputs and outputs. Accordingly, another group of variables is introduced, i.e., level of utilization.

Third, *Level of utilization* may be a better determinant of operational efficiency since it takes into accounts both input and output measures. This case study considers

seven ratio variables, i.e. annual total passengers/land area (PAX/LAND), annual aircraft movements/land area (AIR/LAND), annual aircraft movements/runway (AIR/RW), annual aircraft movements/runway acreage area (AIR/RWA), annual total passengers/number of runways (PAX/RW), annual total passengers/runway acreage area (PAX/RWA), and annual total passengers/annual aircraft movements (PAX/AIR). Intuitively, higher values of these ratios should result in more efficient operation. However the interpretation must be very careful since excessive utilization may imply undesirable congestion and delay. Whenever congested airports are classified as efficient in the results they should not be considered appropriate benchmarks. Instead, other less efficient (Φ near 1) may provide more practical benchmarks.

Fourth, *Market characteristics* include target market (e.g., passengers, aircraft operation, cargo, general aviation and military service), market share, market focus (e.g., domestic, international, tourist, business passengers), and irregularity of time periods. Although such characteristics would be interesting to analyze, collecting them for complete cross-national sample is prohibitively expensive. For example, an attempt was made to collect the percentage of general aviation (GA) operations at airports since serving more GA operations tends to lower operational efficiency (Gillen and Lall, 1997). However, such data are not available for many airports. Similarly, the data are not available for other potential variables. To avoid discarding many airports from the analysis, the entering variables have to be limited to available data. Consequently, three variables, namely the percentage of international passengers (INTER), Y2001 and Y2002 are entered the estimation. It is unclear how this proportion affects airport efficiency.

Y2001 and Y2002 aim at capturing anomalies occurring during these two years, notably the 9-11 terrorist attacks.

Fifth, *Ownership/management characteristics* may be another factor affecting airport efficiency. In particular, the study is interested in two contrasting types of ownership/management, namely publicly-owned and privately-owned. There are some good reasons to argue that the latter type yields higher efficiency. For example, a privately-owned entity faces higher risks. This is likely the case when there is little or no subsidy from public funds. This variable is coded as dummy variable equal to one when the airport is privately-owned or there is strong evidence that it is behaving as a commercialized profit-seeking entity. In the US, Stewart International (SWF) is one such example. It has been privatized to the National Express Group Plc. in 1998 (Steward International Airport, 2005). In London MAS, most airports are of this type. Heathrow (LHR), Gatwick (LGW) and Stansted (STN) have been privatized since 1987 and managed by BAA Plc. City/London (LCY) is owned by an Irish entrepreneur, Dermot Desmond (London City, 2005).

Table 5.2 compares statistics of some candidate variables between efficient (efficiency score = 1) and inefficient airports (efficiency score > 1). It seems clear that an efficient airport uses less input to produce more output, which can be confirmed by its higher utilization variables. However, it is unclear how the proportion of international passengers associates with performance score. Both groups seem to have comparable figures around 20 - 30%. On the management style, privately-operated airports dominate

in the efficient group. For example, in 2002, five out of seven efficient airports are managed commercially.

Table 5.3 shows a Censored Tobit regression model estimation results. The notation is given at the bottom of the Table. This model is a preliminary estimation. It has 11 independent variables, including the constant. Other variables are dropped off for reasons such as high correlation among themselves, being insignificant or having illogical sign. Keep in mind that the lower efficiency score is desirable because it indicates that an airport is more efficient. As a result, a negative sign of estimated coefficient, such as -0.0173 of passengers per aircraft movement (PAX/AIR), contributes to higher efficiency. In this model, passenger market share (PAXSHARE) has an illogical sign. The expected sign should be negative since higher share are more likely associated with higher efficiency.

Year 2001 for which it was aimed to test whether September-11 terrorist attack had any effect on efficiency scores; turns out to be insignificant. Possibly, it did not have immediate effect in that year but propagated to the next year 2002, as Y2002 variable is significant. This means that in 2002, an airport became efficient slightly easier than normal. The marginal effects are also shown next to the right of the coefficient's column. Basically, it indicates the change in efficiency score with respect to unit change of an independent variable. For example, if an airport were able to increase its share of aircraft movements by one percent, it would earn 1.9656 additional units on its efficiency score.

Table 5.2 Comparisons of statistics between efficient and inefficient airports

Variables	2000		2001		2002	
	Efficient (N = 12)	Inefficient (N = 60)	Efficient (N = 14)	Inefficient (N = 58)	Efficient (N = 12)	Inefficient (N = 60)
Land acreage area (LAND)	2,261 (2,896)	2,986 (3,523)	2,161 (2,714)	3,035 (3,567)	1,615 (2,163)	3,115 (3,579)
Number of runways (RW)	2.17 (1.80)	2.80 (1.12)	2.21 (1.67)	2.81 (1.13)	2.42 (1.73)	2.78 (1.18)
Runway acreage area (RWA)	67.13 (68.23)	82.05 (49.54)	68.66 (64.70)	82.32 (49.82)	73.43 (68.60)	82.49 (51.68)
Annual aircraft operations (AIR)	299,963 (294,845)	221,768 (159,866)	287,397 (267,031)	208,485 (150,907)	307,916 (271,078)	197,728 (142,169)
Annual total passengers (PAX)	23,772,828 (28,243,030)	12,121,727 (14,946,553)	23,992,367 (26,255,156)	10,797,422 (12,955,868)	25,620,505 (27,669,409)	10,763,918 (12,608,237)
AIR/LAND	348 (252)	138 (130)	340 (248)	121 (96)	380 (223)	112 (89)
AIR/RW	126,123 (61,830)	74,688 (35,748)	119,697 (55,985)	70,148 (33,350)	117,094 (58,651)	68,035 (30,842)
AIR/RWA	5,505 (3,833)	2,897 (1,496)	5,186 (3,559)	2,678 (1,242)	5,330 (3,665)	2,559 (1,123)
PAX/LAND	12,235 (11,045)	5,426 (6,351)	13,598 (10,672)	4,637 (5,220)	15,287 (11,095)	4,666 (5,346)
PAX/RW	9,442,790 (9,057,704)	3,945,399 (4,267,402)	9,399,439 (8,397,929)	3,513,259 (3,619,718)	8,670,840 (7,874,927)	3,668,420 (3,857,687)
PAX/RWA	290,332 (203,776)	123,563 (118,702)	289,295 (184,177)	110,337 (103,842)	289,748 (204,542)	112,888 (104,246)
PAX/AIR	62.31 (60.97)	45.64 (40.42)	70.12 (68.16)	42.80 (33.24)	63.85 (63.97)	46.23 (37.68)
% of international passenger (INTER)	33.26 (39.73)	22.81 (30.15)	27.97 (37.28)	23.88 (30.59)	24.39 (36.06)	25.09 (31.30)
Management style (MANAGE)	6/6	51/9	8/6	49/9	7/5	50/10

Note: N is the number of airports. Standard deviations are shown in parentheses. For Management style, 7/5 in 2002 represents number of noncommercial (7) and commercial airports (5) respectively.

Table 5.3 Censored Tobit regression: preliminary model estimation results

Variables	Preliminary model $R^2_{ANOVA} = 0.6236$	
	Coefficient	Marginal effect
Constant	6.8560** (17.901)	5.6827** (15.802)
MANAGE	-0.5964* (-2.409)	-0.4943* (-2.419)
PAX/AIR	-0.0173** (-2.917)	-0.0144** (-2.899)
INTER	0.0236** (6.186)	0.0195** (6.040)
AIRSHARE	-2.3715** (-3.343)	-1.9656** (-3.327)
PAXSHARE	0.2955 (0.583)	0.2450 (0.583)
Y2001	-0.3108 (-1.451)	-0.2576 (-1.452)
Y2002	-0.4226* (-1.973)	-0.3503* (-1.974)
PAX/RWA (million/acre)	-4.4344* (-2.260)	-3.6755* (-2.265)
AIR/AREA (1,000/acre)	-6.0155** (-6.731)	-4.9861** (-6.738)
AIR/RWA (1,000/acre)	-0.5530** (-5.237)	-0.4584** (-5.255)
Number of airports = 216 during 2000 - 2002		

Notation:

Dependent variable = Efficiency score

MANAGE = 1 if privately-owned or commercially managed, otherwise = 0

PAX/AIR = Average number of passengers per aircraft movement

INTER = Percentage of international passenger (%)

AIRSHARE = Market share of annual aircraft movements

PAXSHARE = Market share of annual total passengers

Y2001 = 1 if compute performance score in year 2001, otherwise = 0

Y2002 = 1 if compute performance score in year 2002, otherwise = 0

PAX/RWA = Annual total passengers per runway area (million/acre)

AIR/AREA = Annual aircraft movements per land area (10^3 /acre)

AIR/RWA = Annual aircraft movements per runway area (10^3 /acre)

** Estimated coefficient is significant at the 0.01 level (one-tailed)

* Estimated coefficient is significant at the 0.05 level (one-tailed)

Table 5.4 Censored Tobit regression: proposed model estimation results

Variables	Proposed model $R^2_{ANOVA} = 0.6206$	
	Coefficient	Marginal effect
Constant	6.5319** (18.616)	5.4222** (16.326)
MANAGE	-0.6494** (-2.637)	-0.5391** (-2.651)
PAX/AIR	-0.0169** (-2.899)	-0.0140** (-2.880)
INTER	0.0241** (6.424)	0.0200** (6.259)
AIR50	-0.7025** (-2.727)	-0.5831** (-2.716)
PAX50	-0.5858* (-2.405)	-0.4863* (-2.411)
Y2001	-0.3374 (-1.593)	-0.2800 (-1.594)
Y2002	-0.4634* (-2.184)	-0.3846* (-2.186)
PAX/RWA (million/acre)	-4.5793* (-2.349)	-3.8013* (-2.354)
AIR/AREA (1,000/acre)	-5.6768** (-6.551)	-4.7123** (-6.575)
AIR/RWA (1,000/acre)	-0.5760** (-5.515)	-0.4781** (-5.532)
Number of airports = 216 during 2000 - 2002		

Notation:

Dependent variable = Efficiency score

MANAGE = 1 if privately-owned or commercially managed, otherwise = 0

PAX/AIR = Average number of passengers per aircraft movement

INTER = Percentage of international passenger (%)

AIR50 = 1 if the market share of aircraft movements > 50%, otherwise = 0

PAX50 = 1 if the market share of annual total passengers > 50%, otherwise = 0

Y2001 = 1 if compute performance score in year 2001, otherwise = 0

Y2002 = 1 if compute performance score in year 2002, otherwise = 0

PAX/RWA = Annual total passengers per runway area (million/acre)

AIR/AREA = Annual aircraft movements per land area (10^3 /acre)

AIR/RWA = Annual aircraft movements per runway area (10^3 /acre)

** Estimated coefficient is significant at the 0.01 level (one-tailed)

* Estimated coefficient is significant at the 0.05 level (one-tailed)

Table 5.4 shows the final model estimation results. It is the proposed model that may be used for predicting the efficiency score. Instead of using market share like the preliminary model in Table 5.3, the proposed model considers market dominance as an exploratory variable in order to capture the effects of market characteristics. Market dominance is represented by a dummy variable, equal to 1 if an airport has market share more than 50%. There are two market dominance variables i.e. dominance by aircraft movements share (AIR50) and dominance by passenger share (PAX50). As observed previously, market dominance tends to be associated with efficient airports. They turn out to be significant, as observed. The reason may be that an airport is in a better position to utilize its inputs, given higher traffic. Most of the estimated coefficients, except Y2001, are meaningful and significant at above the 95% confidence level. Privately-operated airports (MANAGE = -0.6494) tend to be more efficient than their publicly-operated counterparts, possibly due to higher risk and higher accountability of the management. All utilization ratio variables contribute to higher efficiency, as expected. Proportion of international passengers is negatively associated with the efficiency score. A higher proportion of international passengers lead to lower efficiency. There might be some effect from anomaly in 2001 as Y2001 becomes stronger, though not yet significant enough. The model captures the anomaly in 2002, a year after September-11, where variable Y2002 is significant. The negative sign indicates that an airport becomes efficient slightly more easily in 2002. The marginal effect suggests that for every additional million passenger per acre, an airport would be more efficient by 3.8013 units.

In summary, the first attempt to assess productivity of airports operating in multiple airports systems is presented in this case study. The samples consist of 72 airports in 25

MASs worldwide. The analysis period is during 2000 – 2002. The DEA-Output-VRS model is used as an analytical tool. Five indicators were considered, i.e., land area, number of runways, runway area, number of passengers and number of aircraft movements. The results indicate that there are two groups of efficient or highly productive airports, coined by the busy and the compact. The busy group consists of market leaders in large MASs such as O'Hare International (ORD), Los Angeles International (LAX) and Heathrow/London (LHR). Airports in the compact group are mostly alternative airports with relatively small land area and one or two runways. The reason that both are classified as efficient airports is mainly due to their relatively higher runway utilization. In this respect, larger size of airport does not guarantee high efficiency. It is also found that some airports are under utilized such as Montreal-Mirabel (YMX), Glasgow Prestwick International (GLA), Schoenefeld/Berlin (SXF), and Tempelhof/Berlin (THF). In fact, Montreal-Mirabel (YMX) is a case study of an unsuccessful airport in textbooks (Caves and Gosling, 1999; de Neufville, 1995; de Neufville and Odoni, 2003). Schoenefeld/Berlin (SXF), and Tempelhof/Berlin (THF) and Tegel (TXL, another airport in the Berlin MAS) are planned to be consolidated in 2011. Construction is underway (Berlin Brandenburg International, 2005). In this sense, the proposed models in this case study are useful in pointing out over-investment.

Furthermore, a productivity prediction model was developed by using the Censored Tobit Regression. It is found that factors such as utilization of land area and runway area, passengers per aircraft movement, market dominance and privately-operated management style contribute to the enhancement of productivity. Meanwhile a higher proportion of international passengers tends to reduce the productivity. The model also captures anomaly effects in the year 2002 such that an airport could become efficient slightly more easily with

the same utilization rate, possibly due to a global drop in air traffic after September 11 terrorist attacks. Given some planned measures, the model can be used to predict future total productivity of an airport which should be very useful as a tool for planning airport business in a competitive market.

An important observation from this case study is that an efficient airport needs to be very busy. Some efficient airports are in fact constrained and show sign of undesirable congestion. Like previous airport studies listed in Tables 2.2, 2.3 and 2.4, the downside of facilities and quality of service are still out of consideration. This may be due to the inapplicability of the DEA models to take into account such measures. In the next case study, this issue will be addressed by considering joint production of desirable and undesirable outputs from airport operations. Given that delay data are available for U.S. airports, the case study will be to assess productivity of U.S. airports using delays as a proxy of undesirable outputs. The results should provide a more complete total productivity index.

CHAPTER 6

CASE STUDY 2

PRODUCTIVITY OF U.S. AIRPORTS

Results from case study 1 indicate that ignoring the downside of facilities and quality of service from the assessment typically leads to the conclusion that efficient airports must be very busy. Such results may provide an inappropriate benchmark for managing other airports. In practice, other important output measures reflecting quality of services are always taken into account. Among them, delay is perhaps a major concern. This chapter describes the second case study where the productivity assessment will take undesirable outputs, i.e., delays into consideration.

6.1 Modeling airport operations

An airport may be viewed as a production unit. As a result, airport operation can be modeled as a production process that requires some inputs for running day-to-day operations in order to produce some target outputs. Necessary inputs include production factors such as capital and labor. Most airport managers set target to maximize movement of aircrafts, passenger throughput and quantity of cargo transported. These outputs are highly desirable and the primary reason for building an airport. However, production of these outputs is always constrained by capacity. As the air traffic volume increases, the likely by-product output is higher delays. An airport manager also wants to make sure that the undesirable by-products from the airport operation are being kept at the minimal possible level. Furthermore, an airport is bound to comply with rules and regulations which ensure that its operation does

not create unacceptable externalities, notably noise and pollution. In this situation, where on one hand an airport manager wants to maximize desirable outputs and on the other hand minimize undesirable outputs, the directional output distance function is perfectly applicable.

6.2 Inputs and outputs of airport operations

The formulation of the directional output distance function as shown in linear programming in (3.7) requires data on quantity of inputs, desirable outputs, and undesirable outputs, (x^k, y^k, b^k) for individual airports. The selection of inputs and outputs is an important decision issue in the assessment of airport productivity. The general suggestion is to include all important measures that are in the interest of the management. Such measures should be common for all airports so that the performance would provide meaningful interpretation. In practice, the main problem is the availability of the data across all airports rather than model limitations. After all, three common physical inputs are considered in this analysis:

x_1 = Land area, acre

x_2 = Number of runways

x_3 = Runway area, acre

These inputs may be rather limited due to the availability of data, but they are necessary infrastructure for all airports. Land area (acre) represent considerable share of capital investment that an airport should fully utilize. Number of runways counts all existing runways at the airport regardless of their utilization level. Runway area is the summation of the length x width product of all runways. Runway area is included to reflect the effect of design configuration such as length, width, and separation on productivity.

For the set of desirable outputs, it is assumed that airport managers aim at producing the following three outputs as much as possible:

$$y_1 = \text{Non-delayed flights}$$

$$y_2 = \text{Passengers}$$

$$y_3 = \text{Cargo throughput}$$

All outputs are considered on annual basis. A flight is counted as non-delayed if it is operated no later than 15 minutes from the scheduled time according to Federal Aviation Administration (FAA)'s definition (FAA, 2005 – 2006). The non-delayed flights include all kinds of movements, i.e., commercial aircrafts, cargo aircrafts, general aviation, and others. The number of passengers counts both arriving and departing passengers for all type of commercial passengers, i.e., international, domestic and direct transit passengers. Cargo throughput is measured in metric tones of both loaded and unloaded freight which includes international freight, domestic freight, and mail.

On the set of undesirable output, it is assumed that an airport manager wants to minimize the following two outputs:

$$b_1 = \text{delayed flights}$$

$$b_2 = \text{time delays}$$

Again, both undesirable outputs are on annual basis. Delayed flights are those movements that are operated more than 15 minutes later than the scheduled time. One might argue that delayed flights are not necessarily undesirable from the economics perspective because the passengers still can get to their destinations as they wish. However, airport

managers and passengers may have a different perspective. If they have a choice,, they probably prefer to avoid experiencing delayed flights. As a result, the delayed flights are treated as undesirable outputs.

As a matter of fact, individual delayed flights may incur different delayed times; more of delayed flights does not necessarily mean lower operational efficiency. It also depends on time duration of total delays. Therefore, the time delay (b_2) is included to reflect another perspective of delays. Time delays are the accumulation of delays experienced by individual delayed flights.

Given the above-selected three inputs, three desirable outputs and two undesirable outputs, the assessment may be perceived as the measurement of productive efficiency of airside operation. A question may arise regarding the selection of land area as an input measure. One might argue that acquisition of land area is not purely for improving airside operation, but for other purposes as well. For instance, an airport may prefer to possess more land than needed as noise buffer or for future expansion. It is possible that an airport may seek investment opportunities beyond aeronautical activities such as land value appreciation, or even commercial development. Nevertheless, land area is somehow under management control and the manager can affect productivity of airside operation by managing it efficiently. More importantly, the assessment of productivity is an exploratory analysis which provides information for further judgment, not an ultimate conclusion for implementation. If an airport is found to be inefficient because of inefficient use of any measure, the manager still can reason against the findings. To account for its effect on productivity, the scenario analysis will be done for with and without consideration of land area.

6.3 Sample characteristics

6.3.1 Size of sample

The case study is to assess the relative productivity of major U.S. commercial airports and examine the impact of the inclusion of undesirable outputs on the productivity, ranking and productivity index. Due to readily available data, part of samples are taken from previous airport productivity studies (Pathomsiri and Haghani, 2004; Pathomsiri, Haghani and Schonfeld, 2005; Pathomsiri, Haghani, Dresner and Windle, 2006a). Additional samples are collected in order to increase the sample size. Overall, there are 56 airports in the dataset. This is a relatively high number compared to most previous studies (Abbott and Wu, 2002; Adler and Berechman, 2001; Bazargan and Vasigh, 2003; Fernandes and Pacheco, 2001, 2002, 2005; Gillen and Lall, 1997, 1998; Hooper and Hensher, 1997; Martin and Roman, 2001; Martin-Cejas (2002); Murillo-Melchor, 1999; Nyshadham and Rao, 2000; Oum, Yu and Fu, 2003; Pacheco and Fernandes 2003; Parker, 1999; Pels, Nijkamp and Rietveld, 2001, 2003; Salazar de la Cruz, 1999; Sarkis, 2000; Sarkis and Tulluri, 2004; Yoshida, 2004; Yu, 2004). Table 6.1 lists all 56 airports along with the International Civil Aviation Organization (ICAO) airport codes.

Nevertheless, the number of samples is checked against several applicable rules of thumb to guarantee the sufficiency and meaningful interpretation. For non-parametric approach, DEA provides a very good guideline. As mentioned earlier in Chapter 4, an excessive number of measures with respect to the total number of DMUs may deteriorate the discriminatory power of DEA model. The larger the number of input and output measures for a given number of airports the less discriminatory the DEA model becomes. Given a certain set of samples, this means that the addition of measures will reduce the discriminatory power

of the DEA model. Essentially, this is because it is possible that an airport may dominate all others on one measure, which in turn makes it looked equally efficient to other efficient airports. This is a major issue encountered by Parker (1999), Adler and Berechman (2001) and Yu (2004). To avoid this problem, the straightforward way is to guarantee that there will be sufficient number of airports for comparison with, regarding any measures.

Boussofiene, Dyson and Thanassoulis (1991) recommend that the total number of DMUs be much greater than the number of inputs times the number of outputs. Compared to this analysis where three inputs and five (three desirable plus two undesirable) outputs are selected for the assessment of airport productivity; the number of samples needs to be much more than 3×5 or 15 airports in order to reduce the chance that an airport may be too dominant compared to the others on a particular measure. According to the recommendation, the sample size of 56 airports is deemed satisfactory.

To avoid losing discriminatory power, Cooper, Seiford and Tone (2000: page 103) recommend that the desired number of DMUs exceed $m + s$ several times. They suggest a more stringent rule of thumb in the following formula (Cooper, Seiford and Tone, 2000: page 252).

$$n \geq \max\{m \times s, 3(m + s)\} \quad (6.1)$$

where n is the number of DMUs, while m and s are the numbers of input and output measures, respectively.

Substituting m and s , yields the minimum number of samples:

$$n \geq \max\{3 \times 5, 3(3 + 5)\} = \max\{15, 24\} = 24 \quad (6.2)$$

Again, the sample size of 56 satisfies this recommendation. After all, it can be concluded that the sample size is sufficient for the analysis. Figure 6.1 shows the locations of the sample. Note that these 56 airports are major U.S. commercial airports which regularly appeared at the top of the published statistics from trade publications (ACI, 2002 – 2004). Many of them are in the top twenty according to statistics on annual aircraft movement, passengers, and cargo throughput.

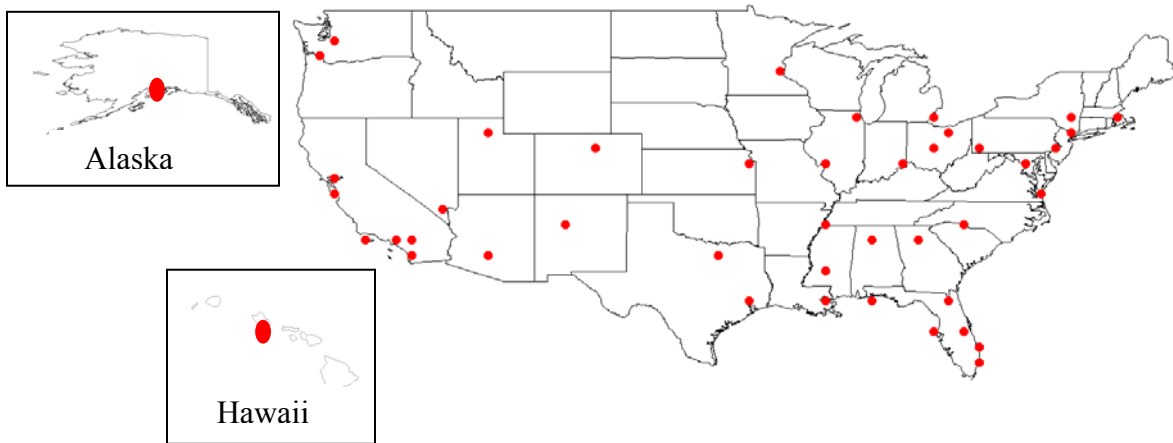


Figure 6.1 Locations of 56 airports

6.3.2 Analysis period

In order to obtain timely results, a recent 4-year panel data for the years 2000 through 2003 are collected. Coincidentally, the period spans the critical time before and after September 11 terrorist attacks which severely affected the aviation industry worldwide. As a result, it allows for analyzing airport productivity to understand its effect on productivity of U.S. airports.

6.3.3 Data source and definition

Input measures were collected from the Airport Master Record database (FAA, 2004) which records physical characteristics of U.S. airports. The database is revised on a regular basis to reflect input changes at airports (e.g., the addition of runways). The data was verified with airport managers, airports' websites and reports, to determine if there were major changes in runway characteristics during the analysis period. There was no change in land area during the analysis period. However, it was found that some airports had improved their runways. For example, George Bush Intercontinental (IAH) expanded and extended runway 15R/33L from 6038' x 100' to 10000' x 150' in 2002. Detroit Metropolitan Wayne County (DTW) opened its 6th runway on December 11, 2001. The number of runways and runway area were then edited accordingly. They were computed precisely by the time the runway improvement was in service during the year, rounding down in month. In the case of DTW, it was recorded that the airport has 5 and 6 runways in 2001 and 2002 respectively.

All airports in the dataset are well-established, having been built and served their respective markets for a number of years. This knowledge helps to relieve concerns about possible sudden productivity drops during the early years after initial lumpy investments. It may be assumed, with caution, that any temporal changes in productivity that might be observed result from operational performance.

Data on the three desirable outputs, i.e., annual statistics on number of passengers, cargo throughput, and aircraft movements are published by the Airports Council International (ACI, 2002 - 2004). Note that aircraft movements include both delayed and non-delayed flights. Given the assumption that an airport manager wishes to maximize only non-delayed flights, the data on delayed flights needed to be collected as well.

There are two available delay database; the Airline Service Quality Performance (ASQP) database maintained by the Bureau of Transportation Statistics (BTS) and the FAA's Operational Network (OPSNET) database (FAA, 2005). In both databases, a flight is counted as delayed if it is operated more than 15 minutes later than the scheduled time, according to the FAA's definition,

The ASQP database contains delays reported by 18 certified U.S. air carriers that have at least one percent of total domestic scheduled-service passenger revenues, plus other carriers that report on a voluntarily basis. The reports cover non-stop scheduled-service flights between points within the U.S., including territories. So far, the carriers report monthly on operations at 31 U.S. airports that account for at least one percent of the nation's total domestic scheduled-service enplanements. The up-to-date list of reportable airlines and airports can be viewed at BTS's website (BTS, 2006). In June 2003, the airlines began reporting the causes of delays in five broad categories, namely (BTS 2004 - 2006; FAA 2006):

1) Air carrier: the cause of the cancellation and delay was due to circumstances within the airline's control (e.g., maintenance or crew problems, aircraft cleaning, baggage loading, fueling, etc.).

2) Extreme weather: significant meteorological conditions (actual and forecast) that, in the judgment of the carrier, delays or prevents the operation of a flight (e.g., tornado, blizzard, hurricane, etc.).

3) National aviation system (NAS): delays and cancellations attributable to the national aviation system that refer to a broad set of conditions – non-extreme weather conditions, airport operations, heavy traffic volume, air traffic control, etc.

4) Late-arriving aircraft: a previous flight with the same aircraft arrived late, causing the present flight to depart late.

5) Security: delays or cancellations caused by evacuation of a terminal or concourse, re-boarding of aircraft because of security breach, inoperative screening equipment and/or long lines in excess of 29 minutes at screening areas.

In broad classification, delays caused by 1) air carrier, 2) extreme weather and 4) late-arriving aircraft are attributable to operation of airlines. Meanwhile, 3) NAS and 5) security delays are from airport operation. According to the recent statistics (BTS, 2005), the proportion of delay causes are 25.6, 4.8, 39.6, 29.7 and 0.3 % for air carrier, extreme weather, NAS, late-arriving aircraft and security respectively. This means that about 60% of delayed flights are caused by airline operation and the rest of 40% are from airport operation.

The other delay database, OPSET is an official source of historical National Aviation System (NAS) air traffic delays and covers a broad set of causes, such as non-extreme weather conditions, airport operations, heavy traffic volume, terminal volume, air traffic control, runway, equipment and others. The OPSNET database is chosen because of two main reasons. First, the analysis focuses on airport operation, rather than airline operations being the source of the delay as in the BTS database. Second, the OPSET database is more complete, covering all flights, all flight types (both domestic and international), all airlines (U.S. and non-U.S. carriers), and all airports in the sample. On the contrary, if ASQP database was used, there would be a large number of under-reported flights since it is based on the sampling report. The numbers of under-reported flights are varying depending on airports. For instance, ASQP database reported only 79.97% of flights at O'Hare International airport in 2003. The missing 21.03% of flights were resulted from non-reportable airlines,

international flights, unclear report, incomplete data, missing value and so on. The figure is quite different at the Baltimore/Washington International airport where 50.86% of total movements are not reported. Inherently, the ASQP database contained biased delay data due to different sampling rates across airports.

Table 6.1 List of 56 US airports under consideration and their outputs in 2003

	Airport name	Airport code	Total passengers	Cargo (tons)	Aircraft movements	Non delayed flights	Delayed flights
1	Hartsfield-Jackson Atlanta International	ATL	79,086,792	798,501	911,723	874,203	37,520
2	O'Hare International	ORD	69,508,672	1,510,746	928,691	859,506	69,185
3	Los Angeles International, CA	LAX	54,982,838	1,833,300	622,378	620,178	2,200
4	Dallas/Fort Worth International, TX	DFW	53,253,607	667,574	765,296	755,873	9,423
5	Denver International, CO	DEN	37,505,138	325,350	499,794	498,469	1,325
6	Phoenix Sky Harbor International, AZ	PHX	37,412,165	288,350	541,771	529,971	11,800
7	McCarran International, NV	LAS	36,285,932	82,153	501,029	494,332	6,697
8	George Bush Intercontinental, TX	IAH	34,154,574	381,926	474,913	458,924	15,989
9	Minneapolis/St. Paul International, MN	MSP	33,201,860	315,987	510,382	503,049	7,333
10	Detroit Metropolitan Wayne County, MI	DTW	32,664,620	220,246	491,073	486,231	4,842
11	John F. Kennedy International, NY	JFK	31,732,371	1,626,722	280,302	274,217	6,085
12	Miami International, FL	MIA	29,595,618	1,637,278	417,423	412,559	4,864
13	Newark Liberty International, NJ	EWR	29,431,061	874,641	405,808	381,159	24,649
14	San Francisco International, CA	SFO	29,313,271	573,523	334,515	325,205	9,310
15	Orlando International, FL	MCO	27,319,223	193,037	295,542	294,300	1,242
16	Seattle Tacoma International, WA	SEA	26,755,888	351,418	354,770	352,786	1,984
17	Philadelphia International, PA	PHL	24,671,075	524,485	446,529	432,902	13,627
18	Charlotte/Douglas International, NC	CLT	23,062,570	140,085	443,394	440,079	3,315
19	Boston Logan International, MA	BOS	22,791,169	363,082	373,304	369,452	3,852
20	LaGuardia, NY	LGA	22,482,770	28,402	374,952	357,054	17,898
21	Covington/Cincinnati/Northern Kentucky International, KY	CVG	21,228,402	392,695	505,557	498,577	6,980
22	Lambert-St. Louis International, MO	STL	20,427,317	115,574	379,772	374,984	4,788
23	Baltimore/Washington International, MD	BWI	20,094,756	235,576	299,469	297,733	1,736
24	Honolulu International, HI	HNL	19,732,556	421,930	319,989	319,976	13
25	Salt Lake City International, UT	SLC	18,466,756	216,870	400,452	399,680	772
26	Midway International, IL	MDW	18,426,397	23,266	328,035	323,041	4,994
27	Fort Lauderdale - Hollywood International, FL	FLL	17,938,046	156,449	287,593	283,700	3,893
28	Washington Dulles International, VA	IAD	16,767,767	285,352	335,397	329,552	5,845
29	Tampa International, FL	TPA	15,523,568	93,457	233,601	232,471	1,130
30	San Diego International, CA	SAN	15,260,791	135,547	203,285	202,506	779

Table 6.1 List of 56 US airports under consideration and their outputs in 2003 (Continued)

	Airport name	Airport Code	Total passengers	Cargo (tons)	Aircraft movements	Non delayed flights	Delayed flights
31	Pittsburg International, PA	PIT	14,266,984	121,536	361,329	360,619	710
32	Ronald Reagan Washington National, DC	DCA	14,214,803	5,774	250,802	249,056	1,746
33	Oakland International, CA	OAK	13,548,363	597,383	342,871	342,567	304
34	Portland International, OR	PDX	12,395,938	239,265	267,052	266,872	180
35	Memphis International, TN	MEM	11,437,307	3,390,515	402,258	400,683	1,575
36	Mineta San Jose International, CA	SJC	10,677,903	108,622	198,082	197,855	227
37	Cleveland Hopkins International, OH	CLE	10,555,387	95,761	258,460	256,993	1,467
38	Kansas City International, MO	MCI	9,715,411	136,687	170,758	170,722	36
39	Louis Armstrong New Orleans International, LA	MSY	9,275,690	80,831	137,312	137,094	218
40	John Wayne, CA	SNA	8,535,130	12,050	350,074	348,475	1,599
41	William P. Hobby, TX	HOU	7,803,330	5,775	242,635	242,084	551
42	Ontario International, CA	ONT	6,547,877	518,710	146,413	146,212	201
43	Port Columbus International, OH	CMH	6,252,061	10,766	237,979	237,915	64
44	Albuquerque International Sunport Airport, NM	ABQ	6,051,879	71,599	221,003	220,962	41
45	Palm Beach International, FL	PBI	6,010,820	18,300	171,692	169,836	1,856
46	Jacksonville International, FL	JAX	4,883,329	70,650	121,143	121,043	100
47	Anchorage International, AK	ANC	4,791,431	2,102,025	277,361	277,165	196
48	Bob Hope, CA	BUR	4,729,936	44,654	178,079	177,902	177
49	Norfolk International, VA	ORF	3,436,391	32,283	121,373	121,330	43
50	Long Beach, CA	LGB	2,875,703	50,873	338,807	338,727	80
51	Birmingham International, AL	BHM	2,672,637	34,184	154,849	154,781	68
52	Pensacola Regional, FL	PNS	1,361,758	4,569	127,197	127,195	2
53	Palm Spring International, CA	PSP	1,246,842	103	93,068	93,032	36
54	Jackson International, MS	JAN	1,215,093	10,957	79,377	79,376	1
55	Santa Barbara, CA	SBA	752,762	2,825	152,485	152,434	51
56	Stewart International, NY	SWF	393,530	19,024	112,284	112,277	7
	Total		1,094,725,865	22,599,243	18,781,482	18,485,876	295,606

The OPSNET database recorded both the number of delayed flights and time delays, which are two undesirable outputs in the analysis. Given the number of delayed flights from OPSNET database, the number of non-delayed flights (one of desirable outputs) is simply the difference between aircraft movements and number of delayed flights.

Table 6.1 presents output measures of 56 airports in 2003. The figures are ordered by number of annual passengers. At the top of the list, Hartsfield-Jackson Atlanta (ATL) is the busiest airport in terms of passengers. O'Hare International (ORD) serviced the highest number of aircraft movements. Memphis International (MEM), the FedEx hub, had the highest cargo throughput. On the downside, ORD experienced the highest number of delayed flights. As shown in Figure 6.2, the number of delayed flights tends to increase with number of passengers serviced at the airport. In fact, there are always externalities inherent in airport operations, notably delay and noise that increase, *ceteris paribus*, with airport volume. These externalities are also outputs from the production process, although undesirable.

In Figure 6.3 density of aircraft movement (number of flights per runway area) is plotted against average delay per passenger, computed for 56 airports in the dataset during 2000 – 2003. This graph shows that higher density of traffic is associated with higher average delay. According to these results, airport efficiency may come at the cost of numerous delays. This situation may be undesirable from the viewpoints of airports, regulators, airlines, and passengers.

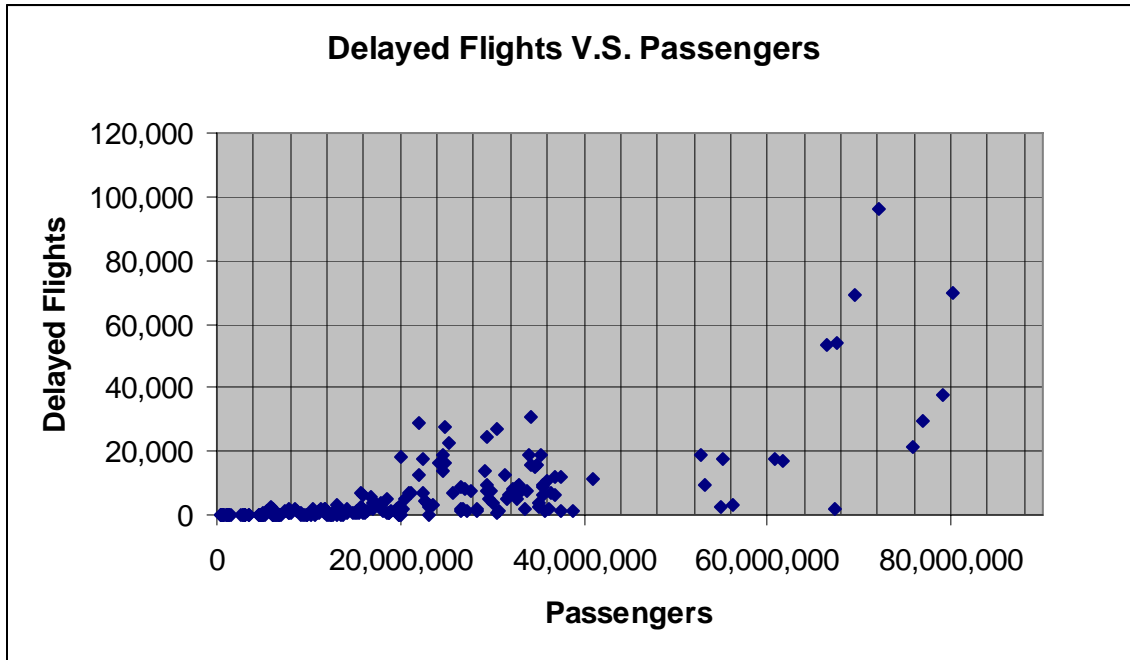


Figure 6.2 Scatter plot between number of delayed flights and number of passengers, 2003

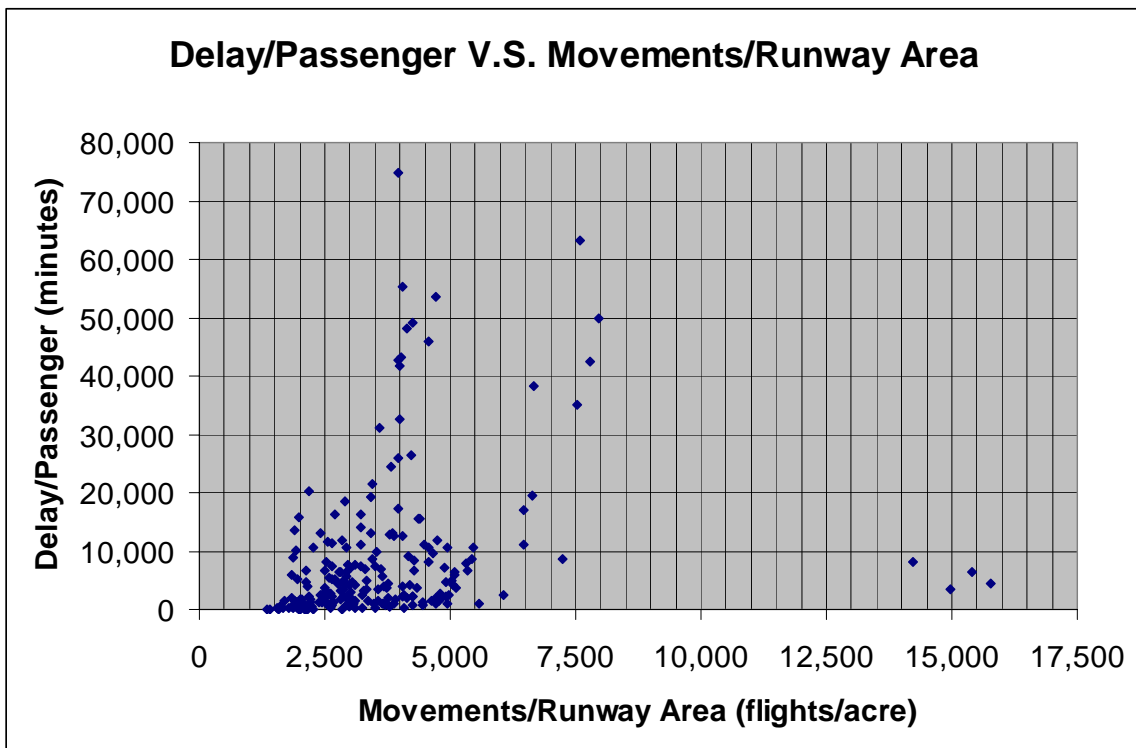


Figure 6.3 Scatter plot between delay/passenger and density of movements, 2000 – 2003

Table 6.2 summarizes the descriptive statistics on input and output measures. All measures show large standard deviations suggesting that airports in the sample vary in both scale and scope of operations. During the study period, all airports experienced at least some flight delays and delays are positively associated with air traffic volume, as scatter plot shows in Figure 6.2. This suggests that delays are important undesirable byproducts that should be taken into consideration when assessing airport productivity.

In the next chapter, results from assessing productivity of 56 airports by the directional output distance function will be presented. The assessment will be discussed with respect to operational efficiency of individual airports. In addition, changes of productivity over analysis period, as well as the impact of the inclusion of undesirable outputs (i.e., delayed flights and time delays) on productivity and ranking of airports will be discussed.

Table 6.2 Descriptive statistics of samples 2000 – 2003

Statistics	Input			Desirable outputs			Undesirable outputs	
	Land area (acre)	Number of runways	Runway area (acre)	Total passengers	# of non delayed flights	Cargo throughput (tons)	# of delayed flights	Time delays (minutes)
Minimum	501	1.00	24.60	362,017	79,376	74	1	20
Maximum	33,422	7.00	305.87	80,162,407	874,203	3,390,800	96,346	5,398,921
Range	32,921	6.00	281.26	79,800,390	794,827	3,390,726	96,345	5,398,901
Mean	4,381	3.35	104.21	20,009,558	343,324	401,667	5,818	259,558
Median	2,650	3.00	99.56	16,225,655	326,086	171,349	1,355	57,200
Standard deviation	5,298	1.21	51.65	16,924,416	176,881	591,702	11,917	611,968

CHAPTER 7

CASE STUDY 2

RESULTS AND DISCUSSION

7.1 Impact of the inclusion of undesirable outputs

For each year (2000 – 2003), the directional output distance function in formulation (3.7) is solved 56 times; i.e., one time for each airport, to determine the optimal efficiency score β^* . β^* , or the distance from the efficient frontier, measures the level of inefficiency. An efficient airport will have $\beta^* = 0$. The higher value of β^* shows greater inefficiencies.

There are several cases in the case study. Case 1 is for the case that considers delayed flights and time delays as undesirable outputs. The sets of inputs and outputs are as follows:

Case 1: with consideration of undesirable outputs

Input = {land area, number of runway, runway area}

Desirable outputs = {non-delayed flights, passengers, cargo}

Undesirable outputs = {delayed flights, time delays}

In order to analyze the effect of the inclusion of undesirable outputs on productive efficiency, a model that ignores undesirable outputs is also solved. Suppose that Case 2 is for the case that does not consider undesirable outputs. The sets of inputs and outputs are as follows:

Case 2: without undesirable outputs or Case 1 – {delayed flights, time delays}

Input = {land area, number of runway, runway area}

Desirable output = {aircraft movements, passengers, cargo}

Undesirable output = {none}

Aircraft movements are the total number of operations both landings and take-offs, regardless of delay status. To assess airport productivity for this case, the model (3.7) needs to be modified accordingly. Specifically, the model in (3.7) is modified by taking out the constraints associated with undesirable outputs, resulting in the following model:

$$\begin{aligned}
 & \max \beta \\
 & s.t. \\
 & \sum_{k \in K} \lambda_k y_{km} \geq (1 + \beta) y_{km}, m = 1, \dots, M, \\
 & \sum_{k \in K} \lambda_k x_{kn} \leq x_{kn}, n = 1, \dots, N, \\
 & \lambda_k \geq 0, k = 1, \dots, K
 \end{aligned} \tag{7.1}$$

The model described in (7.1) is also solved 56 times, each time for an individual airport. Table 7.1 shows efficiency scores for the two cases annually during the period 2000 – 2003. In the Table, airports are ordered alphabetically by their corresponding airport codes. An efficient airport must yield a score of zero, implying that increases in desirable outputs or decreases in undesirable outputs and inputs from current levels are not necessary. In Table 7.1 the efficient airports are highlighted with bold typeface. Several observations can be made from the results. They are discussed in the following sections.

7.1.1 Classification of efficient airports

When delayed flights and time delays are ignored (Case 2), the results are typical of those reported in past studies which suggest that operational efficiency is associated with busy airports (Adler and Berechman, 2001; Bazargan and Vasigh, 2003; Fernandes and Pacheco, 2002; Gillen and Lall, 1997, 1998; Martin and Roman, 2001; Oum and Yu, 2003; Pacheco and Fernandes, 2003; Pathomsiri and Haghani, 2004; Pathomsiri, Haghani and Schonfeld, 2005; Pathomsiri, Haghani, Dresner and Windle, 2006; Pels, Nijkamp and Rietveld, 2003; Sarkis, 2000; as well as Sarkis and Talluri, 2004. As is evident from the 2003 data, six efficient airports are also very busy. For examples, Hartsfield-Jackson Atlanta (ATL) and Memphis (MEM), respectively, are the busiest airports in the world in terms of number of passengers and cargo throughput. LaGuardia (LGA) is one of the most chronically congested airports in the U.S. (CRA, 2001). John Wayne airport (SNA) constrains the number of passengers using its facilities.

Other well-known busy airports such as Anchorage International (ANC), Newark Liberty International (EWR), John F. Kennedy International (JFK), Midway International (MDW), Miami International (MIA), O'Hare International (ORD), Seattle Tacoma International (SEA) and Lambert-St. Louis International (STL), though not classified as efficient, show very low inefficiency level. They all earn relatively low efficient scores (less than 0.5). The implication of these results is that an airport that is very busy or constrained is generally determined to be efficient.

Table 7.1 Efficiency scores for Case 1 and Case 2

Airport code	2000		2001		2002		2003	
	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
ABQ	0.2034	2.6026	0.0000	2.3279	0.0000	2.1394	0.1459	2.5656
ANC	0.0000	0.2314	0.0000	0.0506	0.0000	0.2719	0.0000	0.1607
ATL	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
BHM	0.0000	2.0490	0.0000	1.8211	0.0000	1.8425	0.0000	1.7062
BOS	0.5044	0.9495	0.5901	1.0133	0.5707	1.1142	0.5366	1.1994
BUR	0.0108	1.4154	0.0000	1.3685	0.0000	1.2516	0.0000	0.9675
BWI	0.0000	1.7999	0.0000	1.6086	0.0000	1.6914	0.0000	1.7879
CLE	0.4323	1.4892	0.4745	1.7279	0.6814	2.1009	0.5329	1.9452
CLT	0.3502	0.6097	0.1170	0.4057	0.2693	0.4162	0.2139	0.4722
CMH	0.0000	1.0697	0.0000	0.7945	0.0000	0.7010	0.0000	0.8564
CVG	0.4044	0.5496	0.3123	0.7237	0.2028	0.3720	0.1445	0.3526
DCA	0.0102	0.7610	0.3270	0.9666	0.0831	1.0714	0.0000	0.8962
DEN	0.2956	1.2381	0.0263	1.2805	0.0723	1.2264	0.0370	1.4323
DFW	0.7486	0.9718	0.6133	0.9455	0.7380	1.0190	0.5632	1.0848
DTW	0.6938	1.2993	0.4017	1.1319	0.6783	1.6990	0.5520	1.7536
EWR	0.0000	0.0892	0.0000	0.2055	0.0362	0.1541	0.0000	0.1417
FLL	0.5941	0.8739	0.1505	0.7538	0.3577	0.7183	0.3649	0.7067
HNL	0.0000	1.6907	0.0000	1.6235	0.0000	1.5242	0.0000	1.5904
HOU	0.3367	2.0979	0.3014	2.0753	0.4408	2.0687	0.3063	2.0455
IAD	0.4777	0.6289	0.2531	0.6822	0.4155	0.7778	0.4017	1.0388
IAH	0.5179	0.8696	0.0000	0.8391	0.5056	0.9481	0.6074	0.9998
JAN	0.0000	4.2904	0.0000	3.6530	0.0000	4.1563	0.0000	4.4356
JAX	0.5331	2.2758	0.3636	2.2219	0.5007	2.4574	0.4274	2.6094
JFK	0.3099	0.3469	0.2767	0.4730	0.3642	0.4246	0.2737	0.3759
LAS	0.5919	0.6444	0.0045	0.6896	0.2138	0.6718	0.4974	0.6483
LAX	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
LGA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
LGB	0.0000	1.1960	0.0000	1.2235	0.0000	1.2579	0.0000	1.2281
MCI	0.2827	2.4069	0.1933	2.1817	0.2980	2.4846	0.3422	2.9981
MCO	0.2619	0.9268	0.0000	1.0137	0.0383	1.1632	0.1094	1.1712
MDW	0.0118	0.3364	0.0000	0.2882	0.0000	0.1665	0.0000	0.1177
MEM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 7.1 Efficiency scores for Case 1 and Case 2 (Continued)

Airport code	2000		2001		2002		2003	
	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
MIA	0.0000	0.0301	0.0000	0.0000	0.0000	0.0229	0.0000	0.1650
MSP	0.1833	0.3488	0.0393	0.2947	0.2002	0.2750	0.1709	0.2884
MSY	0.1553	2.6039	0.0000	2.4819	0.0000	2.4938	0.1366	2.6035
OAK	0.0000	0.5276	0.0000	0.5457	0.0000	0.6508	0.0000	0.7313
ONT	0.0000	1.2123	0.2388	1.2000	0.0000	1.0546	0.1085	1.0359
ORD	0.2600	0.5309	0.1223	0.4958	0.0000	0.4646	0.0000	0.4776
ORF	0.2944	2.5854	0.0000	2.4231	0.0331	2.2075	0.1202	2.2866
PBI	0.6936	2.2824	0.2441	2.1645	0.6013	2.5192	0.6686	2.4350
PDX	0.0000	1.1367	0.0000	1.1653	0.0000	1.2548	0.0000	1.3765
PHL	0.7166	0.6512	0.5415	0.6293	0.0000	0.5628	0.6064	0.5875
PHX	0.0000	0.0000	0.0000	0.1491	0.0000	0.1590	0.0000	0.1739
PIT	0.2264	1.2968	0.1214	0.9713	0.3194	1.0942	0.3257	1.5232
PNS	0.1525	2.7395	0.0000	2.4767	0.0000	2.0497	0.0000	2.0909
PSP	0.4099	4.0613	0.7247	3.7163	0.0000	3.5666	0.0000	3.0955
SAN	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
SBA	0.0000	2.4880	0.0000	2.5483	0.0000	2.4674	0.0000	2.4552
SEA	0.0000	0.0821	0.0000	0.0873	0.0000	0.1816	0.0000	0.2607
SFO	0.5650	0.7716	0.4686	0.9830	0.7539	1.1199	0.7767	1.2892
SJC	0.0000	0.8666	0.0000	0.8341	0.3169	1.1352	0.0000	1.3895
SLC	0.6842	1.6591	0.2175	1.3735	0.1123	1.1670	0.1898	1.2490
SNA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
STL	0.0000	0.3992	0.2189	0.3213	0.3945	0.4253	0.5103	0.6358
SWF	0.0147	2.5810	0.0512	2.8170	0.0000	2.4968	0.0000	2.9040
TPA	0.4392	1.5896	0.0294	1.4895	0.1627	1.6490	0.3630	1.8012
Average score	0.2208	1.1813	0.1326	1.1296	0.1672	1.1591	0.1792	1.2168
Number of efficient airports	23	7	29	7	29	6	28	6

Note: An efficient airport has a zero score as highlighted by bold typeface. The input set of both cases are the same. The output set of Case 2 consist of passengers, aircraft movements, and cargo throughput. The output set of Case 1 include passengers, non-delayed flights, cargo throughput, delayed flights, and time delays.

On the contrary, when delayed flights and time delays are also considered (Case 1), the results show a greater number of efficient airports, including less-congested airports. In 2003, totally 28 airports are identified as efficient, as shown in Table 7.1. The additional 22 airports received credit due to their relatively low numbers of delayed flights and total time delays. The different classification is a result of overemphasis on increasing desirable outputs and not giving credit to airports with good performance on controlling undesirable outputs.

The results indicate that there may be a balance between quantity and quality of outputs in the achievement of efficient outcomes; i.e., airports can trade-off utilization levels for reduced flight and time delays. For certain stakeholders, this option may be an optimal strategy. Passengers and shippers receive services with fewer flight delays. The FAA, as the regulator, has less concern over congestion and safety. Meanwhile, airport managers are able to balance traffic volume with customer satisfaction. By all accounts, the inclusion of undesirable outputs in the analysis appears to provide a fairer assessment of airport productivity.

7.1.2 The number of efficient airports

The results also show that the number of efficient airports increases as the number of measured outputs increases. The results are in line with Salazar de la Cruz (1999) who also found that as the number of variables (inputs and outputs) increases, the number of efficient airports is likely to be more. In 2000, without consideration of delayed flights and time delays (Case 2), only seven efficient airports are identified i.e., Hartsfield-Jackson Atlanta (ATL), Los Angeles International (LAX), LaGuardia (LGA), Phoenix Sky Harbor International (PHX), San Diego International (SAN) and John Wayne (SNA).

With the consideration of delayed flights and time delays as undesirable outputs (Case 1), there are 23 efficient airports or 16 more. The increase in the number of efficient airports as outputs are added is partly due to the way efficient units are calculated using non-parametric linear programming methods. The greater the number of outputs, the less likely an airport is to be dominated on all outputs; thus the more likely it is to be on the efficient frontier. As pointed out earlier in Chapter 3 the best way to avoid domination is to have a sufficiently large sample size so that an airport at least has some peers for comparison. This is of course a case in this dissertation.

7.1.3 Difference in efficiency scores

In order to show that efficiency scores are significantly different between Cases 1 and 2, several statistical tests are applied to the results. Tests are performed on both yearly basis and all years. Table 7.2 provides the results from paired-sample t-tests by treating efficiency scores as random variables. The results strongly support the assertion of differences. The efficiency scores in Case 2 are statistically higher than in Case 1. To avoid restricted assumptions of t-test, the non-parametric Wilcoxon signed-rank test and sign test are also performed. The results are shown in Table 7.3. They confirm that the difference in efficiency scores between cases with and without consideration of undesirable outputs is significant.

7.1.4 Ranking

The efficiency scores can be used to rank the performance of airports. All efficient airports (score = 0) are equally efficient since they all are on the efficient frontier. The inefficient airports are ranked in descending order by their efficiency scores. Table 7.4 shows ranking of airport productivity during 2000 – 2003. As shown in the

Table rankings are drastically different when cases with and without consideration of undesirable outputs are compared. For example, by accounting for delays (Case 1) the operational efficiency of Boston Logan International (BOS) is ranked 25th, 54th, 46th, and 49th during 2000 – 2003 as compared to 29th, 31st, 29th, and 31st when ignoring delays (Case 2). This indicates that by not accounting for delayed flights and time delays, the performance ranking of airports can be distorted.

Table 7.2

Comparisons of efficiency scores between Cases 1 and 2 by paired sample t-test

Paired-sample t-test	Paired differences Cases 1 and 2					t
	Mean	Std. deviation	Std. error mean	95% confidence interval of the difference		
				Lower	Upper	
Pair 1: year 2000	0.9605	1.0109	0.1351	0.6898	1.2312	7.110
Pair 2: year 2001	0.9971	0.9211	0.1231	0.7504	1.2437	8.100
Pair 3: year 2002	0.9919	0.9571	0.1279	0.7356	1.2482	7.755
Pair 4: year 2003	1.0377	0.9872	0.1319	0.7733	1.3020	7.866
Pair 5: 2000 – 2003	0.9968	0.9635	0.0644	0.8699	1.1236	15.484

Table 7.3

Comparisons of efficiency scores between Cases 1 and 2 by nonparametric paired tests

Nonparametric paired test		Z	Asymptotic significance (2-tailed)
A. Wilcoxon Signed-Rank test	Pair 1: year 2000	-6.053 ^a	0.000
	Pair 2: year 2001	-6.093 ^a	0.000
	Pair 3: year 2002	-6.154 ^a	0.000
	Pair 4: year 2003	-6.144 ^a	0.000
	Pair 5: 2000 – 2003	-12.189 ^a	0.000
B. Sign test	Pair 1: year 2000	-6.571	0.000
	Pair 2: year 2001	-6.857	0.000
	Pair 3: year 2002	-6.930	0.000
	Pair 4: year 2003	-6.647	0.000
	Pair 5: 2000 – 2003	-13.716	0.000

^a Based on positive ranks.

Table 7.4 Ranking of airport productivity

Airport code	2000		2001		2002		2003	
	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
ABQ	1	52	1	49	1	46	34	53
ANC	1	11	1	8	1	11	1	8
ATL	1	1	1	1	1	1	1	1
BHM	46	44	1	44	1	44	1	44
BOS	25	29	54	31	46	29	49	31
BUR	1	38	1	38	26	38	1	38
BWI	43	43	1	41	1	43	1	41
CLE	40	39	52	43	43	39	48	43
CLT	1	19	35	15	40	19	37	15
CMH	41	31	1	24	1	31	1	24
CVG	24	18	47	22	41	18	33	22
DCA	37	23	48	28	25	23	1	28
DEN	56	35	31	37	37	35	29	37
DFW	54	30	55	27	56	30	51	27
DTW	1	37	50	33	54	37	50	33
EWR	51	10	1	11	1	10	1	11
FLL	1	27	38	23	51	27	43	23
HNL	39	42	1	42	1	42	1	42
HOU	45	45	46	45	39	45	39	45
IAD	47	20	44	20	45	20	44	20
IAH	1	26	1	26	47	26	53	26
JAN	48	56	1	55	1	56	1	55
JAX	38	46	49	48	48	47	45	48
JFK	50	13	45	16	38	13	38	16
LAS	1	21	30	21	50	21	46	21
LAX	1	1	1	1	1	1	1	1
LGA	1	1	1	1	1	1	1	1
LGB	35	33	1	36	1	33	1	36
MCI	34	48	39	47	35	49	41	47
MCO	26	28	1	32	34	28	30	32
MDW	1	12	1	12	27	12	1	12

Table 7.4 Ranking of airport productivity (Continued)

Airport code	2000		2001		2002		2003	
	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
MEM	1	1	1	1	1	1	1	1
MIA	30	8	1	1	1	8	1	1
MSP	29	14	33	13	31	14	35	13
MSY	1	53	1	52	30	53	32	51
OAK	1	16	1	18	1	16	1	18
ONT	33	34	42	35	1	34	29	35
ORD	36	17	37	17	33	17	1	17
ORF	53	51	1	50	36	52	31	49
PBI	1	47	43	46	53	48	54	46
PDX	55	32	1	34	1	32	1	34
PHL	1	22	53	19	55	22	52	19
PHX	32	1	1	10	1	1	1	10
PIT	28	36	36	29	32	36	40	29
PNS	42	54	1	51	29	54	1	50
PSP	1	55	56	56	42	55	1	56
SAN	1	1	1	1	1	1	1	1
SBA	1	49	1	53	1	50	1	52
SEA	49	9	1	9	1	9	1	9
SFO	1	24	51	30	49	24	55	30
SJC	52	25	1	25	1	25	1	25
SLC	1	41	40	39	52	41	36	39
SNA	1	1	1	1	1	1	1	1
STL	27	15	41	14	1	15	47	14
SWF	44	50	34	54	28	51	1	54
TPA	31	40	32	40	44	40	42	40
Sum	1,343	1,575	1,190	1575	1320	1,575	1191	1575
Average 56 airports	0.2208	1.1813	0.1326	1.1296	0.2172	1.1731	0.1792	1.1339
Average inefficiency	0.3747	1.3501	0.2749	1.2910	0.3801	1.3406	0.3135	1.2958
# of efficient airports	23	7	29	7	24	7	28	7

Note: An efficient airport has a ranking = 1.

At the bottom of Table 7.4, the average efficiency scores across inefficient airports are shown. In 2003, the average scores are 0.3135 and 1.2958 for Cases 1 and 2 respectively. These average scores show that the performance of the inefficient airports is about four times poorer if delays are ignored. This result casts a doubt if these airports are really performing that poorly. While these figures may be a result of using incomplete

output measures, they also may be due to ignoring delays that cause unrealistic inefficiency level. This observation leads to another interesting insight next.

7.1.5 Maximum possible production outputs

Another interesting and insightful observation is that by ignoring delayed flights and time delays as outputs, the level of inefficiency may be overestimated. Recall that the terms $(1 + \beta)y_{km}$ plus the corresponding output slacks and $(1 - \beta)b_{kj}$ in (3.7) give the projection of desirable and undesirable outputs onto the frontier. For inefficient airports, these terms represent the maximum possible production outputs or highest potential outputs that an airport could have produced. For an efficient airport with $\beta = 0$, the terms are simply (y_{km}, b_{kj}) or the current level of outputs. It can be seen in Table 7.1 that efficiency scores in Case 2 are much higher than in Case 1. For example, in 2003, Albuquerque International Sunport (ABQ) has a score of 2.5656 in Case 2; implying that ABQ could accommodate at least² 256.56% more passenger trips, aircraft movements and cargo throughput. Meanwhile, in Case 1, ABQ receives a relatively lower score of 0.1459, implying that ABQ would only need to increase all outputs by 14.59% in order to be on the efficient frontier. Overall, in 2003, the average score for these 56 airports suggest that the U.S. airport system should increase all outputs by 17.92% according to the calculations in Case 1 in order to achieve maximum possible production. On the contrary, the system would have had to produce as high as 121.68% more in Case 2.

Tables 7.5, 7.6, 7.7 and 7.8 compare estimated maximum possible production of each airport during 2000 – 2003, for Cases 1 and 2. In each case, the percentage increase

² The maximum possible production outputs may be higher depending on the value of output slacks.

from current levels of outputs is also computed. Let's look at results of the most recent year 2003 (Table 7.8) for explanation. In Case 2, Albuquerque International Sunport (ABQ) had the potential to produce 54,411,318 passengers rather than 6,051,879 that was actually produced in 2003, a 799% increase in passengers. In practice, if ABQ were to produce this high output, it is likely that the number of delayed flights and time delays would be very high and unacceptable. However, after consideration of delayed flights and time delays (Case 1), the maximum possible output at ABQ is just 6,935,011 passengers, or a 14.59% percent increase over the current level.

In general, ignoring undesirable outputs may yield unrealistic maximum possible production outputs. The unrealistic figures occur mainly because the model neglects the relationship between traffic volume, capacity and delay. In practice, delays play a major role in determining acceptable traffic volume and vice versa. The joint consideration of capacity and delays is therefore necessary (de la Cruz, 1999). In certain situations, the capacity of airside operation is limited by environmental considerations (Pels, Nijkamp and Rietveld, 2003).

Based on the results of Case 1, it is suggested that the 56 airports grossly have the potential to increase passengers, aircraft movements (delayed plus non-delayed flights) and cargo throughput by 23.03%, 20.19%, and 34.54%, respectively. If the undesirable outputs are not considered (Case 2), the increases are 133.50%, 90.98% and 363.68%, respectively. The numbers are shown at the end of Table 7.8. The difference of the estimation between Cases 1 and 2 may be interpreted as amount of output loss due to cleaning up delayed flights and time delays or keeping them at relatively low levels.

Table 7.5 Maximum possible passengers, aircraft movements and cargo throughput in 2000

Airport code	Total passengers				Aircraft movements				Cargo (tons)			
	Case 2	% add	Case 1	% add	Case 2	% add	Case 1	% add	Case 2	% add	Case 1	% add
ABQ	31,337,627	398	7,572,239	20	841,169	260	280,925	20	310,571	260	130,936	52
ANC	11,630,465	131	5,030,557	0	355,766	23	288,919	0	2,221,661	23	1,804,221	0
ATL	80,162,407	0	80,162,407	0	915,454	0	915,454	0	868,286	0	868,286	0
BHM	23,268,112	658	3,067,777	0	469,295	205	153,917	0	198,815	388	40,722	0
BOS	54,053,755	95	41,712,092	50	951,353	95	726,532	49	925,906	95	714,502	50
BUR	11,470,266	142	4,800,070	1	388,327	142	162,504	1	90,332	142	62,433	67
BWI	54,885,529	180	19,602,609	0	886,740	180	316,703	0	660,899	180	236,043	0
CLE	33,076,352	149	24,396,829	84	826,156	149	474,220	43	297,305	149	211,276	77
CLT	39,402,365	71	31,173,199	35	727,592	61	607,944	34	351,435	78	287,627	46
CMH	27,704,471	303	6,873,998	0	492,609	107	238,011	0	251,273	1,013	22,572	0
CVG	46,087,079	104	41,581,182	84	740,464	55	665,523	39	605,615	55	644,908	65
DCA	27,978,866	76	16,050,706	1	524,560	76	300,889	1	76,112	102	177,857	371
DEN	86,731,133	124	50,206,299	30	1,144,754	124	739,636	45	1,055,298	124	610,884	30
DFW	119,828,724	97	106,262,017	75	1,651,938	97	1,438,268	72	1,780,819	97	1,579,199	75
DTW	81,705,167	130	70,620,630	99	1,276,964	130	931,597	68	782,621	163	1,325,558	345
EWR	39,629,328	16	34,188,468	0	490,392	9	450,229	0	1,178,964	9	1,082,407	0
FLL	29,719,867	87	25,282,740	59	548,365	87	459,262	57	443,491	87	515,706	118
HNL	65,387,989	184	23,016,542	0	930,378	169	345,771	0	1,187,052	169	441,163	0
HOU	28,205,634	210	12,170,935	34	788,203	210	339,653	33	95,890	1,136	150,134	1,836
IAD	48,445,074	141	42,098,078	109	743,506	63	657,193	44	625,271	63	567,217	48
IAH	65,906,186	87	53,509,212	52	904,086	87	714,538	48	688,946	87	1,146,512	211
JAN	25,459,430	1,772	1,360,280	0	480,811	429	90,883	0	224,726	1,236	16,815	0
JAX	26,717,442	405	8,106,485	53	487,422	228	227,940	53	239,602	293	93,435	53
JFK	44,252,913	35	43,038,655	31	645,887	87	648,506	88	2,449,730	35	2,382,512	31
LAS	60,622,286	64	58,688,340	59	857,227	64	815,812	56	524,591	426	1,060,137	963
LAX	67,303,182	0	67,303,182	0	783,433	0	783,433	0	2,038,784	0	2,038,784	0
LGA	25,374,868	0	25,374,868	0	383,325	0	383,325	0	71,149	0	71,149	0
LGB	18,625,264	2,820	637,853	0	833,152	120	379,399	0	108,514	120	49,415	0
MCI	44,451,860	260	15,841,801	28	743,773	241	279,970	28	513,023	241	244,619	62
MCO	59,390,735	93	38,897,365	26	691,833	93	540,853	51	639,250	136	545,822	101
MDW	20,945,697	34	15,857,218	1	398,415	34	301,469	1	56,849	169	99,464	371
MEM	11,769,213	0	11,769,213	0	388,412	0	388,412	0	2,489,078	0	2,489,078	0

Table 7.5 Maximum possible passengers, aircraft movements and cargo throughput in 2000 (Continued)

Airport code	Total passengers				Aircraft movements				Cargo (tons)			
	Case 2	% add	Case 1	% add	Case 2	% add	Case 1	% add	Case 2	% add	Case 1	% add
MIA	41,331,587	23	33,621,273	0	533,000	3	517,440	0	1,692,142	3	1,642,744	0
MSP	49,589,802	35	43,503,104	18	705,627	35	616,656	18	498,911	35	1,045,794	183
MSY	35,585,902	260	11,407,888	16	575,108	260	184,325	16	311,060	260	164,659	91
OAK	17,638,778	61	10,963,802	0	685,977	53	449,050	0	1,047,067	53	685,425	0
ONT	27,630,613	309	6,757,398	0	344,014	121	155,501	0	1,026,868	121	464,164	0
ORD	110,445,560	53	90,903,872	26	1,391,570	53	1,156,282	27	2,248,207	53	2,437,829	66
ORF	19,038,966	524	3,946,234	29	447,069	259	161,378	29	148,807	414	57,061	97
PBI	22,028,846	277	9,894,942	69	636,289	228	324,876	68	146,000	596	434,258	1,971
PDX	34,705,402	152	13,790,115	0	671,733	114	314,378	0	602,591	114	282,019	0
PHL	41,289,840	66	45,168,996	81	799,671	65	792,038	64	923,560	65	960,161	72
PHX	36,044,635	0	36,044,635	0	579,816	0	579,816	0	340,352	0	340,352	0
PIT	64,079,351	223	26,063,445	32	1,030,784	130	550,159	23	605,070	312	180,292	23
PNS	17,784,319	1,572	3,769,595	254	440,476	274	135,749	15	133,971	2,196	77,276	1,224
PSP	13,963,990	990	3,991,725	212	420,399	406	117,090	41	88,797	67,684	80,433	61,299
SAN	14,868,547	0	14,868,547	0	206,289	0	206,289	0	139,107	0	139,107	0
SBA	12,042,199	1,450	776,904	0	583,806	249	167,376	0	27,912	840	2,970	0
SEA	32,471,210	14	28,408,553	0	482,282	8	445,677	0	494,449	8	456,920	0
SFO	72,724,391	77	64,240,596	56	839,091	95	778,647	81	1,545,324	77	1,707,269	96
SJC	24,447,399	87	13,097,259	0	535,850	87	287,072	0	276,125	87	147,929	0
SLC	56,770,120	185	34,339,104	73	975,732	166	614,373	67	682,341	166	432,166	68
SNA	7,772,801	0	7,772,801	0	387,862	0	387,862	0	15,589	0	15,589	0
STL	42,762,111	40	30,561,387	0	673,060	40	481,025	0	277,661	113	130,152	0
SWF	26,957,370	4,958	8,144,375	1,428	488,683	258	138,470	1	242,439	647	156,004	381
TPA	41,546,269	159	23,090,278	44	719,560	159	399,174	44	383,839	273	421,808	309
Total	2,275,049,295	91	1,551,380,674	30	38,445,502	86	26,008,394	26	37,950,051	59	34,173,774	43

Note: Cases 1 and 2 are with and without consideration of undesirable outputs, respectively. Aircraft movements include both delayed

and non-delayed flights. % add is the percentage increase from current level of the corresponding output.

Table 7.6 Maximum possible passengers, aircraft movements and cargo throughput in 2001

Airport code	Total passengers				Aircraft movements				Cargo (tons)			
	Case 2	% add	Case 1	% add	Case 2	% add	Case 1	% add	Case 2	% add	Case 1	% add
ABQ	47,465,694	668	6,183,606	0	807,793	438	242,733	0	392,202	438	72,876	0
ANC	9,209,894	80	5,107,311	0	298,831	5	284,441	0	1,968,545	5	1,873,750	0
ATL	75,858,500	0	75,858,500	0	890,494	0	890,494	0	739,927	0	739,927	0
BHM	27,516,240	813	3,012,729	0	419,971	597	148,869	0	246,803	597	35,433	0
BOS	48,722,818	101	38,481,290	59	915,317	101	703,723	55	795,525	101	628,306	59
BUR	10,628,250	137	4,487,335	0	378,261	137	159,705	0	77,872	137	32,878	0
BWI	57,724,171	183	20,369,923	0	845,347	161	324,065	0	587,145	161	225,083	0
CLE	36,686,611	209	17,510,135	47	795,772	173	428,372	47	278,267	173	150,411	47
CLT	47,920,880	107	25,890,177	12	648,419	154	514,675	12	450,829	154	292,366	65
CMH	33,859,280	407	6,680,897	0	436,424	2,015	243,201	0	322,739	2,015	15,260	0
CVG	56,893,875	229	22,664,832	31	667,871	72	506,019	31	554,945	72	493,936	53
DCA	25,901,064	97	17,476,832	33	479,876	147	321,934	32	62,278	147	132,195	425
DEN	90,510,082	151	37,043,730	3	1,103,768	144	540,903	12	874,863	144	420,832	17
DFW	129,575,647	135	88,971,994	61	1,524,400	95	1,243,721	59	1,525,449	95	1,378,600	76
DTW	94,823,125	194	45,266,906	40	1,113,118	284	725,372	39	924,909	284	1,442,812	499
EWR	36,838,382	21	30,558,000	0	526,114	21	436,420	0	959,095	21	795,584	0
FLL	28,775,415	75	18,877,562	15	508,702	75	333,261	15	319,020	75	209,287	15
HNL	71,693,282	256	20,151,936	0	857,904	162	327,006	0	885,779	162	337,631	0
HOU	26,562,043	208	11,240,147	30	766,691	2,031	323,801	30	128,895	2,031	74,212	1,127
IAD	56,870,278	218	29,224,387	64	667,618	68	495,596	25	556,658	68	414,667	25
IAH	64,963,714	87	34,803,580	0	866,084	84	470,916	0	621,341	84	337,842	0
JAN	30,870,493	2,304	1,284,311	0	429,945	1,868	92,402	0	288,059	1,868	14,634	0
JAX	32,545,265	541	6,926,081	36	433,576	406	183,398	36	307,492	406	82,896	36
JFK	43,231,654	47	37,470,750	28	616,485	47	598,329	105	2,107,489	47	1,826,652	28
LAS	59,438,371	69	35,338,310	0	834,169	562	530,328	7	530,144	562	517,649	547
LAX	61,606,204	0	61,606,204	0	738,114	0	738,114	0	1,774,402	0	1,774,402	0
LGA	21,933,000	0	21,933,000	0	365,716	0	365,716	0	52,148	0	52,148	0
LGB	15,548,312	2,547	587,473	0	797,136	122	358,508	0	118,267	122	53,190	0
MCI	56,581,449	370	14,358,821	19	667,193	287	250,145	19	551,320	287	236,252	66
MCO	56,893,875	101	28,253,061	0	667,871	148	315,752	0	554,945	148	223,545	0
MDW	20,201,325	29	15,681,966	0	359,062	205	278,734	0	47,809	205	15,684	0
MEM	11,808,247	0	11,808,247	0	394,826	0	394,826	0	2,631,631	0	2,631,631	0

Table 7.6 Maximum possible passengers, aircraft movements and cargo throughput in 2001 (Continued)

Airport code	Total passengers				Aircraft movements				Cargo (tons)			
	Case 2	% add	Case 1	% add	Case 2	% add	Case 1	% add	Case 2	% add	Case 1	% add
MIA	31,668,450	0	31,668,450	0	471,008	0	471,008	0	1,639,760	0	1,639,760	0
MSP	50,445,737	50	35,058,695	4	649,297	40	520,651	4	476,155	40	353,018	4
MSY	33,313,785	248	9,567,651	0	506,842	248	145,564	0	263,581	248	75,700	0
OAK	18,105,026	55	11,713,225	0	611,557	55	395,653	0	917,575	55	593,634	0
ONT	25,557,671	281	8,302,839	24	340,376	120	191,525	24	921,894	120	519,100	24
ORD	100,892,176	50	75,694,280	12	1,364,091	50	1,063,376	17	1,944,048	50	1,567,465	21
ORF	21,572,361	628	2,963,223	0	408,409	522	119,309	0	178,978	522	28,786	0
PBI	24,791,783	317	7,388,932	24	598,280	786	234,992	24	182,456	786	31,619	53
PDX	44,798,994	253	12,703,676	0	630,363	117	291,117	0	526,102	117	242,967	0
PHL	42,669,451	74	37,847,971	54	760,845	63	699,371	50	873,728	63	826,639	54
PHX	45,702,538	29	35,439,051	0	635,807	48	553,310	0	418,347	48	283,337	0
PIT	75,858,500	280	22,365,971	12	890,494	432	506,271	12	739,927	432	155,931	12
PNS	19,880,293	1,781	1,057,150	0	405,037	3,107	116,501	0	159,600	3,107	4,976	0
PSP	16,548,642	1,309	2,025,856	72	396,255	129,894	144,738	72	119,595	129,894	21,966	23,776
SAN	15,184,332	0	15,184,332	0	206,988	0	206,988	0	134,689	0	134,689	0
SBA	11,496,714	1,485	725,140	0	569,460	857	160,486	0	28,190	857	2,946	0
SEA	37,026,987	37	27,036,073	0	435,600	9	400,635	0	435,452	9	400,499	0
SFO	68,676,642	98	50,861,183	47	813,708	98	730,017	88	1,261,208	98	934,037	47
SJC	24,006,781	83	13,088,997	0	468,616	83	255,499	0	263,955	83	143,914	0
SLC	72,645,066	286	22,911,625	22	883,528	224	452,824	22	702,641	224	313,835	45
SNA	7,324,557	0	7,324,557	0	378,903	0	378,903	0	14,849	0	14,849	0
STL	43,567,735	63	36,378,058	36	626,503	219	574,174	21	389,536	219	395,215	223
SWF	32,864,676	8,052	1,918,917	376	434,268	1,463	119,598	5	311,198	1,463	20,924	5
TPA	48,378,795	204	16,355,131	3	649,412	471	268,481	3	456,142	471	217,161	172
Total	2,402,635,134	116	1,280,691,015	15	35,958,516	67	22,772,468	16	35,596,398	67	26,455,537	24

Note: Cases 1 and 2 are with and without consideration of undesirable outputs, respectively. Aircraft movements include both delayed

and non-delayed flights. % add is the percentage increase from current level of the corresponding output.

Table 7.7 Maximum possible passengers, aircraft movements and cargo throughput in 2002

Airport code	Total passengers				Aircraft movements				Cargo (tons)			
	Case 2	% add	Case 1	% add	Case 2	% add	Case 1	% add	Case 2	% add	Case 1	% add
ABQ	47,082,564	665	6,151,129	0	800,139	214	254,874	0	439,749	491	74,460	0
ANC	15,526,628	216	4,914,539	0	352,657	27	277,267	0	2,253,301	27	1,771,595	0
ATL	76,876,128	0	76,876,128	0	889,966	0	889,966	0	734,083	0	734,083	0
BHM	27,861,486	891	2,810,791	0	416,577	184	146,555	0	251,104	676	32,353	0
BOS	47,983,915	111	35,647,876	57	828,929	111	610,900	56	820,220	111	609,352	57
BUR	10,403,788	125	4,620,683	0	365,229	125	162,211	0	89,502	125	39,751	0
BWI	56,209,470	196	19,012,529	0	820,678	169	304,921	0	676,506	169	251,354	0
CLE	36,782,412	252	17,578,887	68	780,673	210	420,585	67	314,417	210	170,482	68
CLT	48,704,535	106	29,952,090	27	645,088	42	576,384	27	446,975	179	280,897	75
CMH	34,377,363	410	6,741,354	0	434,829	70	255,630	0	320,056	2,891	10,700	0
CVG	57,657,096	177	37,620,386	81	667,474	37	582,466	20	550,562	57	420,995	20
DCA	26,662,417	107	13,941,695	8	446,776	107	252,786	17	45,457	675	131,868	2,150
DEN	91,791,939	157	38,229,992	7	1,101,697	123	558,511	13	867,812	161	506,884	52
DFW	132,833,476	151	91,816,824	74	1,544,739	102	1,302,154	70	1,353,342	102	1,165,008	74
DTW	112,639,482	247	54,507,100	68	1,324,897	170	815,124	66	1,081,237	364	764,041	228
EWR	33,702,666	15	30,258,481	4	468,057	15	485,889	20	981,039	15	880,784	4
FLL	29,275,757	72	23,131,236	36	482,401	72	379,747	35	283,600	72	224,076	36
HNL	65,692,610	233	19,749,905	0	817,160	152	323,726	0	1,047,424	152	414,947	0
HOU	24,937,323	210	11,577,573	44	755,604	207	354,136	44	147,858	2,654	99,629	1,756
IAD	56,988,954	234	31,569,526	85	662,482	78	524,229	41	577,566	78	459,860	42
IAH	76,876,128	127	51,048,711	51	889,966	95	743,794	63	734,083	123	514,101	56
JAN	31,395,381	2,471	1,221,138	0	427,372	416	82,883	0	285,553	1,960	13,863	0
JAX	33,066,340	568	7,432,943	50	431,550	246	187,219	50	304,887	342	103,415	50
JFK	42,657,320	42	40,849,751	36	571,199	99	584,615	103	2,264,634	42	2,168,672	36
LAS	58,997,163	69	42,492,287	21	830,639	67	602,418	21	575,288	602	983,493	1,100
LAX	56,223,843	0	56,223,843	0	645,424	0	645,424	0	1,779,855	0	1,779,855	0
LGA	21,986,679	0	21,986,679	0	362,439	0	362,439	0	32,223	0	32,223	0
LGB	17,041,398	1,073	1,453,412	0	791,612	126	350,603	0	120,470	126	53,356	0
MCI	57,345,382	458	13,342,966	30	666,695	248	248,280	30	546,955	303	257,344	89
MCO	57,657,096	116	27,674,633	4	667,475	131	403,408	39	550,562	178	358,923	81
MDW	20,262,756	17	17,371,036	0	354,961	17	304,304	0	30,689	17	26,309	0
MEM	11,141,594	0	11,141,594	0	398,769	0	398,769	0	3,390,800	0	3,390,800	0

Table 7.7 Maximum possible passengers, aircraft movements and cargo throughput in 2002 (Continued)

Airport code	Total passengers				Aircraft movements				Cargo (tons)			
	Case 2	% add	Case 1	% add	Case 2	% add	Case 1	% add	Case 2	% add	Case 1	% add
MIA	30,748,013	2	30,060,241	0	456,445	2	446,235	0	1,661,404	2	1,624,242	0
MSP	50,905,293	56	39,838,014	22	647,262	27	605,830	19	483,388	51	383,425	20
MSY	32,323,453	249	9,251,773	0	486,649	249	139,291	0	294,000	249	84,150	0
OAK	21,470,312	65	13,005,642	0	614,095	65	371,988	0	1,047,698	65	634,643	0
ONT	18,244,259	180	6,517,050	0	306,737	105	149,292	0	1,020,211	105	496,547	0
ORD	100,910,331	52	66,565,952	0	1,351,570	46	922,817	0	2,158,811	46	1,473,980	0
ORF	22,022,803	536	3,579,015	3	402,935	221	129,782	3	180,394	449	52,005	58
PBI	25,628,109	367	8,780,743	60	587,383	252	265,888	59	179,964	906	54,643	205
PDX	45,742,898	274	12,241,975	0	624,291	125	276,877	0	552,719	125	245,134	0
PHL	38,756,685	56	24,799,470	0	723,839	56	463,167	0	845,537	56	541,039	0
PHX	45,950,621	29	35,547,167	0	632,547	16	545,771	0	433,703	45	298,945	0
PIT	76,876,128	326	23,785,515	32	889,966	109	559,932	32	734,083	424	184,943	32
PNS	20,355,106	1,412	1,345,970	0	398,979	205	130,826	0	160,392	3,450	4,518	0
PSP	16,923,015	1,426	1,108,695	0	389,267	357	85,243	0	124,395	168,002	74	0
SAN	14,931,854	0	14,931,854	0	206,380	0	206,380	0	151,644	0	151,644	0
SBA	12,363,316	1,598	728,307	0	554,213	247	159,835	0	26,481	835	2,832	0
SEA	36,563,308	37	26,690,843	0	430,974	18	364,735	0	442,811	18	374,753	0
SFO	66,684,332	112	55,169,980	75	769,286	119	756,932	115	1,250,166	112	1,034,300	75
SJC	23,734,248	114	14,638,695	32	443,072	114	296,477	43	299,251	114	184,570	32
SLC	73,670,012	295	20,741,521	11	881,949	117	452,571	11	696,986	222	297,407	38
SNA	7,903,066	0	7,903,066	0	368,627	0	368,627	0	13,730	0	13,730	0
STL	43,496,722	70	38,825,764	52	623,023	43	604,053	38	416,451	223	352,447	173
SWF	33,385,024	9,122	362,017	0	432,347	250	123,642	0	308,574	2,228	13,257	0
TPA	49,161,407	217	18,015,387	16	646,230	165	283,457	16	452,261	393	268,010	192
Total	2,427,391,404	123	1,323,382,375	22	35,512,220	86	23,101,862	21	37,832,866	70	27,496,714	24

Note: Cases 1 and 2 are with and without consideration of undesirable outputs, respectively. Aircraft movements include both delayed

and non-delayed flights. % add is the percentage increase from current level of the corresponding output.

Table 7.8 Maximum possible passengers, aircraft movements and cargo throughput in 2003

Airport code	Total passengers				Aircraft movements				Cargo (tons)			
	Case 2	% add	Case 1	% add	Case 2	% add	Case 1	% add	Case 2	% add	Case 1	% add
ABQ	54,411,318	799.08	6,935,011	14.59	788,011	256.56	253,241	14.59	331,992	363.68	133,954	87.09
ANC	11,266,457	135.14	4,791,431	0.00	321,940	16.07	277,361	0.00	2,439,876	16.07	2,102,025	0.00
ATL	79,086,792	0.00	79,086,792	0.00	911,723	0.00	911,723	0.00	798,501	0.00	798,501	0.00
BHM	31,529,895	1,079.73	2,672,637	0.00	419,055	170.62	154,849	0.00	233,382	582.72	34,184	0.00
BOS	50,127,482	119.94	35,020,347	53.66	821,054	119.94	569,476	52.55	798,572	119.94	943,554	159.87
BUR	12,125,357	156.35	4,729,936	0.00	350,368	96.75	178,079	0.00	87,856	96.75	44,654	0.00
BWI	59,299,554	195.10	20,094,756	0.00	834,883	178.79	299,469	0.00	656,757	178.79	235,576	0.00
CLE	38,512,358	264.86	16,180,712	53.29	761,211	194.52	394,639	52.69	282,033	194.52	272,944	185.03
CLT	50,223,775	117.77	31,635,406	37.17	652,776	47.22	536,801	21.07	485,352	246.47	334,987	139.13
CMH	35,419,757	466.53	6,252,061	0.00	441,793	85.64	237,979	0.00	347,759	3,130.16	10,766	0.00
CVG	59,315,094	179.41	38,539,652	81.55	683,792	35.26	576,589	14.05	598,876	52.50	449,437	14.45
DCA	26,953,931	89.62	14,214,803	0.00	475,568	89.62	250,802	0.00	37,820	555.01	5,774	0.00
DEN	105,449,056	181.16	38,894,115	3.70	1,215,631	143.23	541,268	8.30	1,064,668	227.24	884,820	171.96
DFW	138,401,886	159.89	83,244,552	56.32	1,595,515	108.48	1,185,676	54.93	1,397,377	109.32	1,043,533	56.32
DTW	115,815,897	254.56	50,696,543	55.20	1,352,208	175.36	756,815	54.11	1,157,774	425.67	710,246	222.48
EWR	33,602,832	14.17	29,431,061	0.00	463,330	14.17	405,808	0.00	998,619	14.17	874,641	0.00
FLL	30,614,102	70.67	24,484,401	36.49	490,823	70.67	389,706	35.51	267,005	70.67	226,674	44.89
HNL	67,258,823	240.85	19,732,556	0.00	828,895	159.04	319,989	0.00	1,092,962	159.04	421,930	0.00
HOU	38,225,686	389.86	10,193,688	30.63	738,946	204.55	316,623	30.49	56,298	874.86	155,183	2,587.15
IAD	59,315,094	253.74	28,154,745	67.91	683,792	103.88	465,444	38.77	598,876	109.87	399,990	40.17
IAH	82,382,075	141.20	54,898,411	60.74	949,711	99.98	743,930	56.65	831,772	117.78	683,510	78.96
JAN	32,391,557	2,565.77	1,215,093	0.00	431,462	443.56	79,377	0.00	309,945	2,728.74	10,957	0.00
JAX	34,088,414	598.06	6,970,535	42.74	437,251	260.94	172,836	42.67	331,134	368.70	104,553	47.99
JFK	43,660,391	37.59	40,417,649	27.37	565,144	101.62	570,852	103.66	2,238,198	37.59	2,071,962	27.37
LAS	62,644,718	72.64	54,332,887	49.74	825,834	64.83	743,556	48.41	523,744	537.52	510,720	521.67
LAX	54,982,838	0.00	54,982,838	0.00	622,378	0.00	622,378	0.00	1,833,300	0.00	1,833,300	0.00
LGA	22,482,770	0.00	22,482,770	0.00	374,952	0.00	374,952	0.00	28,402	0.00	28,402	0.00
LGB	18,447,560	541.50	2,875,703	0.00	754,909	122.81	338,807	0.00	113,352	122.81	50,873	0.00
MCI	58,998,549	507.27	13,040,110	34.22	682,712	299.81	229,168	34.21	594,923	335.24	265,216	94.03
MCO	59,315,094	117.12	30,308,286	10.94	683,792	131.37	380,232	28.66	598,876	210.24	860,080	345.55
MDW	20,595,835	11.77	18,426,397	0.00	366,656	11.77	328,035	0.00	26,160	12.44	23,266	0.00
MEM	11,437,307	0.00	11,437,307	0.00	402,258	0.00	402,258	0.00	3,390,515	0.00	3,390,515	0.00

Table 7.8 Maximum possible passengers, aircraft movements and cargo throughput in 2003 (Continued)

Airport code	Total passengers				Aircraft movements				Cargo (tons)			
	Case 2	% add	Case 1	% add	Case 2	% add	Case 1	% add	Case 2	% add	Case 1	% add
MIA	34,479,734	16.50	29,595,618	0.00	486,310	16.50	417,423	0.00	1,907,475	16.50	1,637,278	0.00
MSP	54,502,729	64.16	41,741,976	25.72	657,595	28.84	595,117	16.60	529,522	67.58	370,000	17.09
MSY	33,425,071	260.35	10,542,505	13.66	494,806	260.35	156,040	13.64	291,276	260.35	253,278	213.34
OAK	23,456,948	73.13	13,548,363	0.00	593,629	73.13	342,871	0.00	1,034,279	73.13	597,383	0.00
ONT	17,639,338	169.39	7,258,006	10.85	298,085	103.59	162,248	10.82	1,056,052	103.59	574,965	10.85
ORD	103,836,235	49.39	69,508,672	0.00	1,372,264	47.76	928,691	0.00	2,232,328	47.76	1,510,746	0.00
ORF	24,266,049	606.15	3,849,419	12.02	398,907	228.66	135,951	12.01	174,884	441.72	36,821	14.06
PBI	31,753,180	428.27	10,029,678	66.86	589,762	243.50	284,004	65.41	254,710	1,291.86	175,200	857.38
PDX	47,653,087	284.43	12,395,938	0.00	634,652	137.65	267,052	0.00	568,616	137.65	239,265	0.00
PHL	39,166,142	58.75	39,631,312	60.64	708,879	58.75	700,772	56.94	832,637	58.75	842,526	60.64
PHX	49,730,463	32.93	37,412,165	0.00	635,974	17.39	541,771	0.00	415,223	44.00	288,350	0.00
PIT	79,086,792	454.33	18,913,688	32.57	911,723	152.32	478,550	32.44	798,501	557.01	294,139	142.02
PNS	22,273,756	1,535.66	1,361,758	0.00	393,148	209.09	127,197	0.00	157,215	3,340.92	4,569	0.00
PSP	20,361,442	1,533.04	1,246,842	0.00	381,163	309.55	93,068	0.00	95,380	92,501.67	103	0.00
SAN	15,260,791	0.00	15,260,791	0.00	203,285	0.00	203,285	0.00	135,547	0.00	135,547	0.00
SBA	13,319,297	1,669.39	752,762	0.00	526,873	245.52	152,485	0.00	24,526	768.17	2,825	0.00
SEA	38,400,771	43.52	26,755,888	0.00	447,256	26.07	354,770	0.00	443,031	26.07	351,418	0.00
SFO	67,104,325	128.92	52,079,506	77.67	767,885	129.55	600,665	79.56	1,312,916	128.92	1,682,768	193.41
SJC	25,514,563	138.95	10,677,903	0.00	473,312	138.95	198,082	0.00	259,549	138.95	108,622	0.00
SLC	75,830,984	310.64	21,972,152	18.98	900,616	124.90	476,174	18.91	757,846	249.45	402,086	85.40
SNA	8,535,130	0.00	8,535,130	0.00	350,074	0.00	350,074	0.00	12,050	0.00	12,050	0.00
STL	47,057,418	130.37	35,870,254	75.60	621,218	63.58	568,680	49.74	378,835	227.79	299,115	158.81
SWF	34,412,038	8,644.45	393,530	0.00	438,355	290.40	112,284	0.00	335,175	1,661.85	19,024	0.00
TPA	50,687,729	226.52	21,158,079	36.30	654,359	180.12	317,570	35.95	491,146	425.53	649,238	594.69
Total	2,556,136,266	133.50	1,346,865,126	23.03	35,868,503	90.98	22,573,542	20.19	39,051,395	363.68	30,404,043	34.54

Note: Cases 1 and 2 are with and without consideration of undesirable outputs, respectively. Aircraft movements include both delayed

and non-delayed flights. % add is the percentage increase from current level of the corresponding output.

7.2 Lumpiness of airport investment

Due to the fact that airport inputs are relatively fixed and air traffic tends to grow over a long period of time, one may expect a rather stable operational efficiency during the analysis. In most cases, this is true as long as there is no asset selling or drastic change in air traffic. Nevertheless, it is possible to see sharp decline in efficiency at some point in time due to the opening of a new facility. In the early years of an asset's life it is likely that excess capacity will prevail and hence show up as a contributing factor to low annual productivity. In the later years of an asset's life it might show up through an impact on high levels of congestion and hence a shortage of capacity which can reduce output and hence affect productivity in a different way (Hooper and Hensher, 1997).

In his study, Parker (1999) explained that the sharp decline during 1991/92 at Stansted, London was associated with the opening of a new terminal in that year, leading to further excess capacity. The technical efficiency can be expected to rise over time and favor later airports over the earlier ones. Similarly, a newly delivered runway may therefore have a capacity that far exceeds realized demand. The lumpiness of runway investments can signify a productivity drop in the early years after the investment, as results indicate in the case of Detroit Metropolitan Wayne County (DTW) which opened its 6th runway on December 11, 2001. During 2000 – 2001, its productivity scores in Table 7.1 are rather stable (i.e., 1.2993 and 1.1319), but downgraded significantly in 2002 and 2003 (i.e., 1.6990 and 1.7536) after the new runway was completed. The same situation occurs at George Bush Intercontinental (IAH) which expanded and extended runway 15R/33L from 6038' x 100' to 10000' x 150'. The scores are rather stable during

2000 – 2001, i.e., 0.8696 and 0.8391) and downgraded afterwards (i.e., 0.9481 and 0.9998 in 2002 and 2003 respectively). Therefore, once the sharp drop is detected, it should not be presumed that it is due to poor management.

7.3 Changes in productivity over time

In the past only Gillen and Lall (1998) studied the productivity growth of U.S. airports during 1989 – 1993 by computing the Malmquist index. As reviewed in Chapter 2, the study did not consider any undesirable outputs. It was explained in Chapter 3 that Malmquist index is not appropriate when there is an undesirable output. Here, the Luenberger (L) productivity index (equation 3.20) is computed with more comprehensive output measures during recent years. Table 7.9 and 7.10 shows the results for Cases 1 and 2 respectively.

Table 7.9 shows computed changes in productivity for each airport and the overall average for 56 airports. Along with Luenberger index, its two components, i.e., efficiency change (LEFFCH) and technical change (LTECHCH) are also shown. Note that these indexes signal improvements with values greater than zero, and declines in productivity with values less than zero. The zero value indicates no productivity change between two years.

Table 7.9 Luenberger productivity indexes, Case 1

Airport code	2000 – 2001			2001 - 2002			2002 - 2003		
	L	LEFFCH	LTECHCH	L	LEFFCH	LTECHCH	L	LEFFCH	LTECHCH
ABQ	0.079	0.203	-0.124	0.009	0.000	0.009	-0.090	-0.146	0.056
ANC	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ATL	0.310	0.000	0.310	0.000	0.000	0.000	0.000	0.000	0.000
BHM	-0.002	0.000	-0.002	0.000	0.000	0.000	0.029	0.000	0.029
BOS	-0.079	-0.086	0.007	-0.023	0.019	-0.042	-0.029	0.034	-0.063
BUR	-0.001	0.011	-0.012	0.000	0.000	0.000	0.000	0.000	0.000
BWI	0.015	0.000	0.015	0.096	0.000	0.096	0.000	0.000	0.000
CLE	-0.127	-0.042	-0.085	-0.068	-0.207	0.139	0.035	0.148	-0.114
CLT	0.040	0.233	-0.193	-0.003	-0.152	0.150	-0.021	0.055	-0.076
CMH	0.000	0.000	0.000	0.012	0.000	0.012	-0.012	0.000	-0.012
CVG	-0.170	0.092	-0.262	0.219	0.110	0.109	0.042	0.058	-0.016
DCA	-0.220	-0.317	0.096	0.091	0.244	-0.153	0.060	0.083	-0.023
DEN	-0.019	0.269	-0.288	0.033	-0.046	0.079	-0.008	0.035	-0.043
DFW	0.023	0.135	-0.112	-0.001	-0.125	0.124	0.055	0.175	-0.120
DTW	0.060	0.292	-0.232	-0.086	-0.277	0.190	-0.052	0.126	-0.178
EWR	0.011	0.000	0.011	0.124	-0.036	0.160	0.050	0.036	0.014
FLL	0.102	0.444	-0.342	-0.045	-0.207	0.162	0.009	-0.007	0.016
HNL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
HOU	-0.073	0.035	-0.108	0.001	-0.139	0.140	0.007	0.134	-0.128
IAD	-0.048	0.225	-0.273	-0.064	-0.162	0.098	-0.055	0.014	-0.069
IAH	0.104	0.518	-0.414	-0.102	-0.506	0.404	-0.032	-0.102	0.070
JAN	0.077	0.000	0.077	0.026	0.000	0.026	0.000	0.000	0.000
JAX	0.042	0.170	-0.127	-0.029	-0.137	0.108	-0.029	0.073	-0.103
JFK	-0.116	0.033	-0.149	0.089	-0.088	0.176	0.043	0.091	-0.048
LAS	0.235	0.587	-0.353	0.017	-0.209	0.226	-0.111	-0.284	0.173
LAX	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LGA	0.475	0.000	0.475	0.001	0.000	0.001	0.173	0.000	0.173
LGB	-0.014	0.000	-0.014	0.000	0.000	0.000	-0.001	0.000	-0.001
MCI	-0.025	0.089	-0.114	-0.062	-0.105	0.042	-0.072	-0.044	-0.028
MCO	-0.015	0.262	-0.277	-0.009	-0.038	0.029	-0.021	-0.071	0.050
MDW	-0.002	0.012	-0.014	0.000	0.000	0.000	0.000	0.000	0.000
MEM	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 7.9 Luenberger productivity indexes, Case 1 (Continued)

Airport code	2000 - 2001			2001 - 2002			2002 - 2003		
	L	LEFFCH	LTECHCH	L	LEFFCH	LTECHCH	L	LEFFCH	LTECHCH
MIA	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
MSP	-0.001	0.144	-0.145	-0.030	-0.161	0.131	-0.002	0.029	-0.031
MSY	-0.012	0.155	-0.168	0.046	0.000	0.046	-0.068	-0.137	0.068
OAK	-0.013	0.000	-0.013	0.000	0.000	0.000	0.000	0.000	0.000
ONT	-0.077	-0.239	0.162	0.069	0.239	-0.170	-0.054	-0.108	0.054
ORD	0.264	0.138	0.126	0.170	0.122	0.047	0.134	0.000	0.134
ORF	0.162	0.294	-0.132	-0.017	-0.033	0.017	-0.047	-0.087	0.040
PBI	-0.078	0.450	-0.527	-0.138	-0.357	0.219	-0.009	-0.067	0.058
PDX	-0.015	0.000	-0.015	0.000	0.000	0.000	-0.003	0.000	-0.003
PHL	0.204	0.175	0.029	0.047	0.541	-0.495	-0.116	-0.606	0.491
PHX	0.265	0.000	0.265	0.020	0.000	0.020	0.008	0.000	0.008
PIT	-0.016	0.105	-0.121	-0.066	-0.198	0.132	-0.138	-0.006	-0.132
PNS	0.023	0.152	-0.130	0.001	0.000	0.001	0.002	0.000	0.002
PSP	-0.056	-0.315	0.259	0.314	0.725	-0.411	0.000	0.000	0.000
SAN	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SBA	-0.010	0.000	-0.010	-0.002	0.000	-0.002	-0.018	0.000	-0.018
SEA	-0.026	0.000	-0.026	0.000	0.000	0.000	0.000	0.000	0.000
SFO	-0.105	0.096	-0.202	0.014	-0.285	0.299	-0.056	-0.023	-0.033
SJC	0.000	0.000	0.000	-0.158	-0.317	0.158	0.019	0.317	-0.298
SLC	-0.061	0.467	-0.528	0.096	0.105	-0.009	-0.056	-0.078	0.022
SNA	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
STL	-0.109	-0.219	0.109	-0.087	-0.176	0.089	-0.171	-0.116	-0.056
SWF	-0.070	-0.037	-0.034	0.191	0.051	0.139	-0.005	0.000	-0.005
TPA	0.066	0.410	-0.344	-0.015	-0.133	0.119	-0.093	-0.200	0.107
Average index	0.018	0.088	-0.070	0.012	-0.035	0.047	-0.013	-0.012	-0.001
Number of regress	28	7	34	19	23	7	27	16	23
Number of no change	9	21	9	15	24	15	15	25	15
Number of progress	19	28	13	22	9	34	14	15	18

Note: Negative index indicates regressed productivity. Zero value means that there is no change in productivity between two years. Positive index indicates productivity growth.

According to the results, the airport system on average had productivity gains in two periods during 2000 – 2002 and productivity loss in 2003. The amount of changes regardless of progress or regress is rather low. Between 2000 and 2001, the overall average rise in efficiency was 1.8 percent; and continued to increase by 1.2 percent in the next period before falling down slightly 1.3 percent during 2002 – 2003. The results are suggesting that productivity of U.S. airports during 2000 – 2003 is more or less the same. At the airport level, only five airports, i.e., Newark Liberty International (EWR), LaGuardia (LGA), O'Hare International (ORD), Phoenix Sky Harbor International (PHX), and Pensacola Regional (PNS) show progress in all periods. For all airports and all periods, it is found that there were productivity losses in 74 cases; productivity remains the same in 39 cases and there were productivity gains in 55 cases. About 32% of all cases show productivity gains. The productivity loss at many airports, especially between 2000 and 2001, may be associated with the September 11 terrorist attacks which shook aviation industry worldwide.

Decomposition of Luenberger index into efficiency change (LEFFCH) and technical change (LTECHCH) can help explain source of productivity gain or loss. The equations for computing LEFFCH and LTECHCH are given in (3.21) and (3.22) respectively. An airport which has been efficient in time period t and $t + 1$, will naturally show no change in relative efficiency. Only Covington/Cincinnati/Northern Kentucky International (CVG) achieved productivity gains in all time periods. For the sample as a whole, efficiency gains occur between 2000 and 2001; then drop afterwards in 2002 and 2003. Between 2000 and 2001 the overall average rise in efficiency was 8.8 percent. This

was followed by a 3.5 % and 1.2 % drops in the two subsequent periods. For all airports and all periods, it is found that there were productivity losses in 46 cases; productivity remains the same in 70 cases and there were productivity gains in 52 cases. About 33% of all cases show productivity gains.

The computed LTECHCH is shown next to LEFFCH column in Table 7.9. LTECHCH measures the average shifts in the efficient frontier from time period t to time period $t+1$. This corresponds to the term in equation (3.22). The results show productivity gain in one period, i.e., 2001 – 2002; and two periods, i.e., 2000 - 2001 and 2002 - 2003 with productivity loss. Between 2000 and 2001, high negative value of LTECHCH (-0.070) indicates that the efficient frontier shifted backward. In other words, for a given level of inputs in 2000, the airport system produces lower outputs in 2001 than in 2000. For all airports and all periods, it is found that there were productivity losses in 64 cases; productivity remains the same in 39 cases and there were productivity gains in 65 cases. About 33% of all cases show productivity gains. About 39% of all cases show productivity gains.

In conclusion, the productivity gains between 2000 and 2001 are mainly from efficiency change (LEFFCH = 0.088) which compensates the productivity loss from frontier shifted backward (LTECHCH = -0.070). The situation is opposite in 2001/2002 period where productivity gains resulted from frontier shift (LTECHCH = 0.047). Between 2002 and 2003 both efficiency loss and frontier backward shift collectively contribute to the overall productivity loss (L = -0.013).

Productivity indexes for Case 2 are also computed in order to analyze the impact of considering undesirable outputs in the assessment. The results are shown in Table 7.10. For convenient comparisons, productivity indexes in Cases 1 and 2 are presented side by side in Table 7.11. For individual airports, the results do not show any recognizable pattern. Moreover, the overall picture of the airport system indicates a different conclusion. Instead of showing productivity gains between 2000 and 2001 ($L = 0.018$), Case 2 shows the opposite result, i.e., productivity loss ($L = -0.041$). The classification of productivity changes is also very different in all periods. It clearly shows the two sets of results are drastically different. Again, this confirms previous findings that ignoring undesirable outputs in the assessment really creates problematic results.

Several statistical tests are performed on the Luenberger indexes to check if the difference between Cases 1 and 2 are statistical different. Table 7.12 provides the results from paired-sample t-tests which strongly support the assertion of differences. To avoid the restricted assumptions of the t-test, the non-parametric Wilcoxon signed-rank test and sign test are also performed. The results are shown in Table 7.13. They confirm that the difference in Luenberger productivity indexes between Cases 1 and 2 is significant. There is one exception in period 2002/03 where Z-statistics from both Wilcoxon signed rank test ($Z = -2.213$) and sign test ($Z = 0.099$) are not significant at 95%.

Table 7.10 Luenberger productivity indexes, Case 2

Airport code	2000 – 2001			2001 – 2002			2002 - 2003		
	L	LEFFCH	LTECHCH	L	LEFFCH	LTECHCH	L	LEFFCH	LTECHCH
ABQ	0.125	0.275	-0.150	0.158	0.189	-0.031	-0.477	-0.426	-0.051
ANC	0.014	0.181	-0.167	-0.029	-0.221	0.192	0.073	0.111	-0.038
ATL	0.000	0.000	0.000	0.000	0.000	0.000	0.012	0.000	0.012
BHM	-0.098	0.228	-0.326	-0.044	-0.021	-0.023	0.153	0.136	0.016
BOS	-0.201	-0.064	-0.138	-0.159	-0.101	-0.059	-0.046	-0.085	0.039
BUR	-0.041	0.047	-0.088	0.061	0.117	-0.056	0.189	0.284	-0.095
BWI	0.040	0.191	-0.151	-0.112	-0.083	-0.029	-0.061	-0.096	0.036
CLE	-0.333	-0.239	-0.094	-0.416	-0.373	-0.043	0.066	0.156	-0.090
CLT	0.031	0.204	-0.173	-0.018	-0.010	-0.007	-0.039	-0.056	0.017
CMH	0.042	0.275	-0.234	0.087	0.093	-0.006	-0.127	-0.155	0.028
CVG	-0.325	-0.174	-0.151	0.350	0.352	-0.002	0.052	0.019	0.033
DCA	-0.319	-0.206	-0.113	-0.106	-0.105	-0.002	0.191	0.175	0.015
DEN	-0.165	-0.042	-0.122	0.050	0.054	-0.004	-0.154	-0.206	0.052
DFW	-0.137	0.026	-0.163	-0.073	-0.073	0.001	0.000	-0.066	0.066
DTW	-0.135	0.167	-0.302	-0.569	-0.567	-0.002	0.001	-0.055	0.056
EWR	-0.119	-0.116	-0.003	-0.017	0.051	-0.068	0.009	0.012	-0.003
FLL	-0.032	0.120	-0.152	-0.005	0.035	-0.041	0.038	0.012	0.027
HNL	-0.203	0.067	-0.270	0.039	0.099	-0.060	-0.018	-0.066	0.048
HOU	-0.068	0.023	-0.090	-0.047	0.007	-0.054	-0.045	0.023	-0.068
IAD	-0.224	-0.053	-0.170	-0.098	-0.096	-0.003	-0.194	-0.261	0.066
IAH	-0.053	0.030	-0.084	-0.114	-0.109	-0.005	-0.004	-0.052	0.048
JAN	0.082	0.637	-0.555	-0.533	-0.503	-0.029	-0.229	-0.279	0.050
JAX	-0.327	0.054	-0.381	-0.251	-0.235	-0.016	-0.106	-0.152	0.046
JFK	-0.177	-0.126	-0.051	0.070	0.048	0.022	0.034	0.049	-0.015
LAS	-0.078	-0.045	-0.033	0.010	0.018	-0.008	0.014	0.024	-0.010
LAX	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LGA	0.000	0.000	0.000	0.000	0.000	0.000	0.008	0.000	0.008
LGB	-0.095	-0.028	-0.067	-0.043	-0.034	-0.009	-0.077	0.030	-0.107
MCI	-0.132	0.225	-0.358	-0.305	-0.303	-0.002	-0.425	-0.514	0.089
MCO	-0.139	-0.087	-0.052	-0.092	-0.149	0.058	0.041	-0.008	0.049
MDW	-0.055	0.048	-0.104	0.096	0.122	-0.026	0.062	0.049	0.013
MEM	0.000	0.000	0.000	0.078	0.000	0.078	0.000	0.000	0.000

Table 7.10 Luenberger productivity indexes, Case 2 (Continued)

Airport code	2000 – 2001			2001 - 2002			2002 - 2003		
	L	LEFFCH	LTECHCH	L	LEFFCH	LTECHCH	L	LEFFCH	LTECHCH
MIA	-0.023	0.030	-0.054	-0.011	-0.023	0.011	-0.132	-0.142	0.010
MSP	-0.051	0.054	-0.105	0.016	0.020	-0.004	0.002	-0.013	0.016
MSY	-0.195	0.122	-0.317	-0.063	-0.012	-0.051	-0.024	-0.110	0.086
OAK	-0.146	-0.018	-0.128	0.011	-0.105	0.116	-0.064	-0.081	0.017
ONT	-0.132	0.012	-0.144	0.088	0.145	-0.057	0.001	0.019	-0.018
ORD	-0.066	0.035	-0.101	0.038	0.031	0.007	0.013	-0.013	0.026
ORF	-0.155	0.162	-0.317	0.171	0.216	-0.045	-0.112	-0.079	-0.033
PBI	-0.081	0.118	-0.199	-0.416	-0.355	-0.061	0.012	0.084	-0.072
PDX	-0.178	-0.029	-0.149	-0.093	-0.089	-0.003	-0.078	-0.122	0.044
PHL	-0.058	0.022	-0.080	-0.009	0.066	-0.075	-0.050	-0.025	-0.026
PHX	-0.201	-0.149	-0.052	-0.016	-0.010	-0.006	-0.009	-0.015	0.006
PIT	0.014	0.326	-0.312	-0.124	-0.123	-0.001	-0.373	-0.429	0.056
PNS	-0.040	0.263	-0.303	0.378	0.427	-0.049	-0.086	-0.041	-0.045
PSP	0.056	0.345	-0.289	0.067	0.150	-0.083	0.380	0.471	-0.091
SAN	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SBA	-0.148	-0.060	-0.088	-0.014	0.081	-0.095	-0.163	0.012	-0.175
SEA	-0.093	-0.005	-0.088	-0.097	-0.094	-0.003	-0.036	-0.079	0.043
SFO	-0.264	-0.211	-0.053	-0.139	-0.137	-0.002	-0.098	-0.169	0.072
SJC	-0.124	0.032	-0.156	-0.263	-0.301	0.038	-0.184	-0.254	0.071
SLC	0.017	0.286	-0.268	0.202	0.207	-0.004	-0.036	-0.082	0.046
SNA	-0.007	0.000	-0.007	-0.007	0.000	-0.007	-0.012	0.000	-0.012
STL	-0.021	0.078	-0.099	-0.112	-0.104	-0.008	-0.215	-0.210	-0.004
SWF	-0.675	-0.236	-0.439	0.304	0.320	-0.016	-0.356	-0.407	0.051
TPA	-0.141	0.100	-0.242	-0.172	-0.160	-0.013	-0.118	-0.152	0.034
Average index	-0.104	0.052	-0.156	-0.041	-0.029	-0.012	-0.050	-0.058	0.008
Number of regress	42	18	51	33	28	43	32	33	18
Number of no change	4	6	4	4	6	4	3	6	3
Number of progress	10	32	1	19	22	9	21	17	35

Note: The negative index indicates regressed productivity. Zero value means that there is no change in the productivity between two years. The positive index indicates productivity growth.

Table 7.11 Comparisons of Luenberger productivity indexes between Cases 1 and 2

Airport code	2000 - 2001		2001 - 2002		2002 - 2003	
	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
ABQ	0.079	0.125	0.009	0.158	-0.090	-0.477
ANC	0.000	0.014	0.000	-0.029	0.000	0.073
ATL	0.310	0.000	0.000	0.000	0.000	0.012
BHM	-0.002	-0.098	0.000	-0.044	0.029	0.153
BOS	-0.079	-0.201	-0.023	-0.159	-0.029	-0.046
BUR	-0.001	-0.041	0.000	0.061	0.000	0.189
BWI	0.015	0.040	0.096	-0.112	0.000	-0.061
CLE	-0.127	-0.333	-0.068	-0.416	0.035	0.066
CLT	0.040	0.031	-0.003	-0.018	-0.021	-0.039
CMH	0.000	0.042	0.012	0.087	-0.012	-0.127
CVG	-0.170	-0.325	0.219	0.350	0.042	0.052
DCA	-0.220	-0.319	0.091	-0.106	0.060	0.191
DEN	-0.019	-0.165	0.033	0.050	-0.008	-0.154
DFW	0.023	-0.137	-0.001	-0.073	0.055	0.000
DTW	0.060	-0.135	-0.086	-0.569	-0.052	0.001
EWR	0.011	-0.119	0.124	-0.017	0.050	0.009
FLL	0.102	-0.032	-0.045	-0.005	0.009	0.038
HNL	0.000	-0.203	0.000	0.039	0.000	-0.018
HOU	-0.073	-0.068	0.001	-0.047	0.007	-0.045
IAD	-0.048	-0.224	-0.064	-0.098	-0.055	-0.194
IAH	0.104	-0.053	-0.102	-0.114	-0.032	-0.004
JAN	0.077	0.082	0.026	-0.533	0.000	-0.229
JAX	0.042	-0.327	-0.029	-0.251	-0.029	-0.106
JFK	-0.116	-0.177	0.089	0.070	0.043	0.034
LAS	0.235	-0.078	0.017	0.010	-0.111	0.014
LAX	0.000	0.000	0.000	0.000	0.000	0.000
LGA	0.475	0.000	0.001	0.000	0.173	0.008
LGB	-0.014	-0.095	0.000	-0.043	-0.001	-0.077
MCI	-0.025	-0.132	-0.062	-0.305	-0.072	-0.425
MCO	-0.015	-0.139	-0.009	-0.092	-0.021	0.041
MDW	-0.002	-0.055	0.000	0.096	0.000	0.062
MEM	0.000	0.000	0.000	0.078	0.000	0.000

Table 7.11 Comparisons of Luenberger productivity indexes (Continued)

Airport code	2000 - 2001		2001 - 2002		2002 - 2003	
	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
MIA	0.000	-0.023	0.000	-0.011	0.000	-0.132
MSP	-0.001	-0.051	-0.030	0.016	-0.002	0.002
MSY	-0.012	-0.195	0.046	-0.063	-0.068	-0.024
OAK	-0.013	-0.146	0.000	0.011	0.000	-0.064
ONT	-0.077	-0.132	0.069	0.088	-0.054	0.001
ORD	0.264	-0.066	0.170	0.038	0.134	0.013
ORF	0.162	-0.155	-0.017	0.171	-0.047	-0.112
PBI	-0.078	-0.081	-0.138	-0.416	-0.009	0.012
PDX	-0.015	-0.178	0.000	-0.093	-0.003	-0.078
PHL	0.204	-0.058	0.047	-0.009	-0.116	-0.050
PHX	0.265	-0.201	0.020	-0.016	0.008	-0.009
PIT	-0.016	0.014	-0.066	-0.124	-0.138	-0.373
PNS	0.023	-0.040	0.001	0.378	0.002	-0.086
PSP	-0.056	0.056	0.314	0.067	0.000	0.380
SAN	0.000	0.000	0.000	0.000	0.000	0.000
SBA	-0.010	-0.148	-0.002	-0.014	-0.018	-0.163
SEA	-0.026	-0.093	0.000	-0.097	0.000	-0.036
SFO	-0.105	-0.264	0.014	-0.139	-0.056	-0.098
SJC	0.000	-0.124	-0.158	-0.263	0.019	-0.184
SLC	-0.061	0.017	0.096	0.202	-0.056	-0.036
SNA	0.000	-0.007	0.000	-0.007	0.000	-0.012
STL	-0.109	-0.021	-0.087	-0.112	-0.171	-0.215
SWF	-0.070	-0.675	0.191	0.304	-0.005	-0.356
TPA	0.066	-0.141	-0.015	-0.172	-0.093	-0.118
Average index	0.018	-0.104	0.012	-0.041	-0.013	-0.050
Number of regress	28	42	19	33	27	32
Number of no change	9	4	15	4	15	3
Number of progress	19	10	22	19	14	21

Note: The negative index indicates regressed productivity. Zero value means that there is no change in the productivity between two years. The positive index indicates productivity growth.

Table 7.12 Comparisons of Luenberger productivity indexes by paired sample t-test

Paired-sample t-test	Paired differences Cases 1 and 2					t
	Mean	Std. deviation	Std. error mean	95% confidence interval of the difference		
				Lower	Upper	
Pair 1: 2000/01	0.1219	0.1458	0.0194	0.0829	0.1610	6.2605
Pair 2: 2001/02	0.0531	0.1527	0.0204	0.0122	0.0940	2.6014
Pair 3: 2002/03	0.0373	0.1287	0.0172	0.0029	0.0718	2.1741
Pair 4: 2000 – 03	0.0708	0.1466	0.0113	0.0484	0.0931	6.2607

Table 7.13 Comparisons of Luenberger productivity indexes by nonparametric tests

Nonparametric paired test		Z	Asymptotic significance (2-tailed)
A. Wilcoxon Signed-Rank test	Pair 1: years 2000/01	-5.307 ^a	0.000
	Pair 2: years 2001/02	-2.598 ^a	0.009
	Pair 3: years 2002/03	-2.213 ^a	0.026
	Pair 4: years 2000 - 03	-6.027 ^a	0.000
B. Sign test	Pair 1: years 2000/01	-4.395	0.000
	Pair 2: years 2001/02	-2.747	0.006
	Pair 3: years 2002/03	-1.648	0.099
	Pair 4: years 2000 - 03	-5.234	0.000

^a Based on positive ranks.

7.4 Scenario analysis

Having shown that ignoring undesirable outputs while assessing productivity of airports can cause drastically different interpretations (sometimes unrealistic), it is interesting to analyze the impact of other measures on productivity. The results will provide more insights on the sensitivity of estimated productivity. Many different sets of possible input and output measures can be analyzed. Pathomsiri, Haghani, Windle and Dresner (2006) have analyzed the impact of cargo throughput and a single undesirable output – delayed flights, on the productivity of 56 U.S. airports (the same dataset that is used in this dissertation). Their work notes that the addition of the undesirable output (delayed flights) into the model made much more difference than the addition of another desirable output (cargo throughput); i.e., higher number of efficient airports are identified. The results suggest that consideration of undesirable output is at least as important as the consideration of additional desirable outputs in determining relative productivity of airports. Here let's consider the effects of an input measure, i.e., land area.

Recall that the preceding sections consider land area as an operational input along with number of runways and runway area. The resulting estimated productivity indicates the operational efficiency of airside operation from utilizing these three inputs. One might argue that land area is not being used solely for airside operation which is probably true. Nowadays many airports are more enthusiastic to provide non-aeronautical services including concessions, rentals and car parking (Francis and Humphreys, 2001; Francis, Humphreys and Fry (2002); Hooper and Hensher, 1997; Humphreys, 1999; Humphreys and Francis, 2002; Nyshadham and Rao, 2000; Oum and Yu, 2004; Oum, Yu and Fu,

2003). In some airports such as Honolulu, Vancouver and Sydney, non-aeronautical revenues account for as much as 70% of their total revenues (Oum and Yu, 2004). Airport management has become more diversified (Francis and Humphreys, 2001). Land area is being utilized beyond just aeronautical services. Furthermore, airport may own more excessive land for other reasons such as noise abatement, planned future expansion, land appreciation, and other investment. In such cases, inclusion of land area in the set of input may give biased results in favor of airports with less land area and limited non-aeronautical activities.

To analyze the impact of land area, Case 3 is then set up as follow:

Case 3: without land area as an input

Input = {number of runway, runway area}

Desirable outputs = {non-delayed flights, passengers, cargo}

Undesirable outputs = {delayed flights, time delays}

The directional output distance function in (3.7) is then solved again 56 times, each for an individual airport to estimate the efficiency score, β . Table 7.14 shows the results. The estimated efficiency scores in Case 1 are copied from Table 7.1 for comparison purposes. There are several interesting observations for discussion.

First, on the efficiency scores, average scores from both cases (at the bottom of the Table) are not much different. The difference is relatively much smaller than the comparison between Cases 1 (with undesirable outputs) and 2 (without desirable outputs). This is because at the individual airports, scores are not different. Several

airports even earned identical scores regardless of cases. In 2003, 45 airports have identical pairs of scores. Only 11 airports (i.e., ABQ, BOS, DCA, FLL, HOU, LGB, MDW, MSY, ONT, and ORF) show different scores. For all of them, the productivity is downgraded. These 11 airports are relatively smaller in land size than those 45. The range of area is between 650 (at MDW) and 2039 (at ABQ) acres. Inclusion of land area as an input clearly favors airports with relatively smaller size.

Second, on the classification of efficient airports, the results show that all efficient airports in Case 3 are also efficient in Case 1. In other words, the set of efficient airports in Case 3 is a subset of efficient airports in Case 1. Excluding land area never decreases inefficiency level in Case 1. Inefficient airports in Case 1 are still identified as (more) inefficient in Case 3. Note that one should not expect this finding to be always true in other applications. It is possible that excluding (or including) an input measure from the consideration may decrease (or increase) inefficiency levels if that input measure is a dominant one.

Third, on the number of efficient airports, the annual figures are not much different. Case 1 identifies 23, 29, 29 and 28 efficient airports whereas Case 3 identifies 22, 24, 24 and 25 airports in 2000, 2001, 2002 and 2003 respectively. Both cases identify almost the same set of efficient airports. Case 1 with more total measures (number of inputs plus outputs) identifies more efficient airports. This finding is in line with previous observations (Parker, 1999; Salazar de la Cruz, 1999; Pathomsiri, Haghani, Dresner and Windle, 2006b, 2006c; Pathomsiri, Haghani, Windle and Dresner, 2006).

Table 7.14 Efficiency scores for Cases 1 and 3

Airport code	2000		2001		2002		2003	
	Case 1	Case 3	Case 1	Case 3	Case 1	Case 3	Case 1	Case 3
ABQ	0.2034	0.5771	0.0000	0.0193	0.0000	0.1729	0.1459	0.4162
ANC	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ATL	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
BHM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
BOS	0.5044	0.5048	0.5901	0.5901	0.5707	0.5713	0.5366	0.5407
BUR	0.0108	0.1478	0.0000	0.0500	0.0000	0.0000	0.0000	0.0000
BWI	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
CLE	0.4323	0.4763	0.4745	0.5047	0.6814	0.6958	0.5329	0.6372
CLT	0.3502	0.3502	0.1170	0.1170	0.2693	0.2693	0.2139	0.2139
CMH	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
CVG	0.4044	0.4044	0.3123	0.3123	0.2028	0.2028	0.1445	0.1445
DCA	0.0102	0.0570	0.3270	0.3445	0.0831	0.1696	0.0000	0.0428
DEN	0.2956	0.2956	0.0263	0.0263	0.0723	0.0723	0.0370	0.0370
DFW	0.7486	0.7486	0.6133	0.6133	0.7380	0.7380	0.5632	0.5632
DTW	0.6938	0.6938	0.4017	0.4017	0.6783	0.6783	0.5520	0.5520
EWR	0.0000	0.0000	0.0000	0.0000	0.0362	0.1011	0.0000	0.0000
FLL	0.5941	0.5941	0.1505	0.1505	0.3577	0.3577	0.3649	0.3654
HNL	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
HOU	0.3367	0.4391	0.3014	0.4138	0.4408	0.4880	0.3063	0.4503
IAD	0.4777	0.4777	0.2531	0.2531	0.4155	0.4155	0.4017	0.4017
IAH	0.5179	0.5179	0.0000	0.0000	0.5056	0.5056	0.6074	0.6074
JAN	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
JAX	0.5331	0.5331	0.3636	0.3636	0.5007	0.5007	0.4274	0.4274
JFK	0.3099	0.3099	0.2767	0.2767	0.3642	0.3642	0.2737	0.2737
LAS	0.5919	0.6252	0.0045	0.0429	0.2138	0.2595	0.4974	0.4974
LAX	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
LGA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
LGB	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0306
MCI	0.2827	0.2827	0.1933	0.1933	0.2980	0.2980	0.3422	0.3422
MCO	0.2619	0.2619	0.0000	0.0000	0.0383	0.0383	0.1094	0.1094
MDW	0.0118	0.6070	0.0000	0.1707	0.0000	0.4767	0.0000	0.5131
MEM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 7.14 Efficiency scores for Cases 1 and 3 (Continued)

Airport code	2000		2001		2002		2003	
	Case 1	Case 3	Case 1	Case 3	Case 1	Case 3	Case 1	Case 3
MIA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MSP	0.1833	0.1833	0.0393	0.0438	0.2002	0.2002	0.1709	0.1709
MSY	0.1553	0.2757	0.0000	0.1037	0.0000	0.0468	0.1366	0.2220
OAK	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ONT	0.0000	0.1934	0.2388	0.3104	0.0000	0.1477	0.1085	0.2135
ORD	0.2600	0.2600	0.1223	0.1223	0.0000	0.0000	0.0000	0.0000
ORF	0.2944	0.2944	0.0000	0.0000	0.0331	0.0408	0.1202	0.1316
PBI	0.6936	0.6936	0.2441	0.2441	0.6013	0.6013	0.6686	0.6686
PDX	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
PHL	0.7166	0.7526	0.5415	0.5620	0.0000	0.6188	0.6064	0.6064
PHX	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
PIT	0.2264	0.2264	0.1214	0.1214	0.3194	0.3194	0.3257	0.3257
PNS	0.1525	0.1525	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
PSP	0.4099	0.4372	0.7247	0.7255	0.0000	0.0000	0.0000	0.0000
SAN	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
SBA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
SEA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
SFO	0.5650	0.5650	0.4686	0.4686	0.7539	0.7539	0.7767	0.7767
SJC	0.0000	0.0000	0.0000	0.0729	0.3169	0.4290	0.0000	0.0000
SLC	0.6842	0.6842	0.2175	0.2175	0.1123	0.1123	0.1898	0.1898
SNA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
STL	0.0000	0.0000	0.2189	0.2189	0.3945	0.3945	0.5103	0.5103
SWF	0.0147	0.0147	0.0512	0.0512	0.0000	0.0000	0.0000	0.0000
TPA	0.4392	0.4392	0.0294	0.0294	0.1627	0.1627	0.3630	0.3630
Average score	0.2208	0.2514	0.1326	0.1453	0.1672	0.2001	0.1792	0.2026
Number of efficient airports	23	22	29	24	29	24	28	25

Note: An efficient airport has a zero score as highlighted by bold typeface. The output sets of Cases 1 and 3 are the same. The input set of Case 3 is {number of runways, runway area}. The input set of Case 1 is {land area, number of runways, runway area}

Both parametric and nonparametric statistical tests are performed to determine whether the score differences between Cases 1 and 3 are significant. Table 7.15 shows results from paired-sample t-test whereas results from nonparametric Wilcoxon signed rank test and sign test are shown in Table 7.16. In brief, paired-sample t-tests infer that efficiency scores in Cases 1 and 3 are still significantly different. However, the level of significance is not as strong as in the comparison between Cases 1 and 2. The t-statistics are as low as -2.1708 (Pair 4: year 2003). Results from nonparametric tests (Table 7.16) also provide the same statistical inference. Both Wilcoxon signed-rank test and sign test indicate the difference in scores in Cases 1 and 3 are statistically significant at 99% level.

Table 7.15

Comparisons of efficiency scores between Cases 1 and 3 by paired sample t-test

Paired-sample t-test	Paired differences Cases 1 and 3					t
	Mean	Std. deviation	Std. error mean	95% confidence interval of the difference		
				Lower	Upper	
Pair 1: year 2000	-0.0305	0.0981	0.0131	-0.0568	-0.0042	-2.3273
Pair 2: year 2001	-0.0127	0.0330	0.0044	-0.0215	-0.0038	-2.8848
Pair 3: year 2002	-0.0328	0.1072	0.0143	-0.0616	-0.0041	-2.2956
Pair 4: year 2003	-0.0234	0.0807	0.0107	-0.0450	-0.0018	-2.1708
Pair 5: 2000 – 2003	-0.0248	0.0845	0.0056	-0.0360	-0.0137	-4.4057

Table 7.16

Comparisons of efficiency scores between Cases 1 and 3 by nonparametric paired tests

Nonparametric paired test		Z	Asymptotic significance (2-tailed)
A. Wilcoxon Signed-Rank test	Pair 1: year 2000	-3.0594 ^a	0.0022
	Pair 2: year 2001	-3.1798 ^a	0.0014
	Pair 3: year 2002	-3.1798 ^a	0.0014
	Pair 4: year 2003	-2.9340 ^a	0.0033
	Pair 5: 2000 – 2003	-6.0927 ^a	0.0000
B. Sign test	Pair 1: year 2000	-	.0004 ^b
	Pair 2: year 2001	-	.0002 ^b
	Pair 3: year 2002	-	.0002 ^b
	Pair 4: year 2003	-	.0009 ^b
	Pair 5: 2000 – 2003	-6.8571	.0000 ^b

^a Based on negative ranks.

^b Binomial distribution used.

Fourth, on the maximum possible production, Tables 7.17, 7.18, 7.19 and 7.20 compare estimated potential outputs from Cases 1 and 3 in 2000, 2001, 2002, and 2003 respectively. Since the two cases tend to identify similar set of efficient airports, it is not surprising to see that the figures are very similar between cases. The difference between two cases only occurs at some airports. For example, in 2003, 11 airports (i.e., ABQ, BOS, DCA, FLL, HOU, LGB, MDW, MSY, ONT, and ORF - those with different efficiency scores) show different maximum possible production. Consequently, the figures for overall system are slightly different. Without land area (Case 3), the system may have potential to accommodate 25, 22, and 42% of passengers, movements and cargo throughput as compared to 23, 20 and 35% when having land area as another input (Case 1). Seemingly, ignoring land area does not drastically change the results. The assessment of 56 U.S. airports tends to be robust. The addition of undesirable outputs

(i.e., delayed flights and time delays) into the model made a much greater difference than the addition of another input (i.e., land area). In the latter case, the model only identifies very few more efficient airports. This finding suggests that consideration of undesirable outputs is at least as important as the consideration of additional inputs in determining the relative productivity of airports.

Fifth, on the productivity growth indexes, Table 7.21 compares computed Luenberger productivity indexes between Cases 1 and 3. Since inputs to the computation (i.e., efficiency scores) are rather similar, the resulting indexes are therefore only slightly different. Between 2000 and 2001, the overall system growth is 0.9% in Case 3 as compared to 1.8% in Case 1. The gaps are narrower in the the two subsequent periods where Case 1 shows growth of 1.2% and -1.3% as compared to 1.3% and -1.0% in Case 3. The significant difference of efficiency scores between two cases are largely hidden in the computation of Luenberger indexes. A caution should be raised here if one were to perform statistical tests on the difference of Luenberger indexes.

Table 7.17 Maximum possible passengers, aircraft movements and cargo throughput in 2000, Cases 1 and 3

Airport code	Total passengers				Aircraft movements				Cargo (tons)			
	Case 1	% add	Case 3	% add	Case 1	% add	Case 3	% add	Case 1	% add	Case 3	% add
ABQ	7,572,239	20	17,571,012	179	280,925	20	368,092	58	130,936	52	288,345	234
ANC	5,030,557	0	5,030,557	0	288,919	0	288,919	0	1,804,221	0	1,804,221	0
ATL	80,162,407	0	80,162,407	0	915,454	0	915,454	0	868,286	0	868,286	0
BHM	3,067,777	0	3,067,777	0	153,917	0	153,917	0	40,722	0	40,722	0
BOS	41,712,092	50	41,722,480	50	726,532	49	726,709	49	714,502	50	714,680	50
BUR	4,800,070	1	5,508,388	16	162,504	1	184,494	15	62,433	67	49,499	32
BWI	19,602,609	0	19,602,609	0	316,703	0	316,703	0	236,043	0	236,043	0
CLE	24,396,829	84	21,725,198	63	474,220	43	488,684	47	211,276	77	407,440	241
CLT	31,173,199	35	31,173,199	35	607,944	34	607,944	34	287,627	46	287,627	46
CMH	6,873,998	0	6,873,998	0	238,011	0	238,011	0	22,572	0	22,572	0
CVG	41,581,182	84	41,581,182	84	665,523	39	665,523	39	644,908	65	644,908	65
DCA	16,050,706	1	16,793,926	6	300,889	1	314,654	6	177,857	371	295,216	682
DEN	50,206,299	30	50,206,299	30	739,636	45	739,636	45	610,884	30	610,884	30
DFW	106,262,017	75	106,262,017	75	1,438,268	72	1,438,268	72	1,579,199	75	1,579,199	75
DTW	70,620,630	99	70,620,630	99	931,597	68	931,597	68	1,325,558	345	1,325,558	345
EWR	34,188,468	0	34,188,468	0	450,229	0	450,229	0	1,082,407	0	1,082,407	0
FLL	25,282,740	59	25,282,740	59	459,262	57	459,262	57	515,706	118	515,706	118
HNL	23,016,542	0	23,016,542	0	345,771	0	345,771	0	441,163	0	441,163	0
HOU	12,170,935	34	14,351,543	58	339,653	33	365,560	44	150,134	1,836	145,628	1,778
IAD	42,098,078	109	42,098,078	109	657,193	44	657,193	44	567,217	48	567,217	48
IAH	53,509,212	52	53,509,212	52	714,538	48	714,538	48	1,146,512	211	1,146,512	211
JAN	1,360,280	0	1,360,280	0	90,883	0	90,883	0	16,815	0	16,815	0
JAX	8,106,485	53	8,106,485	53	227,940	53	227,940	53	93,435	53	93,435	53
JFK	43,038,655	31	43,038,655	31	648,506	88	648,506	88	2,382,512	31	2,382,512	31
LAS	58,688,340	59	59,913,693	63	815,812	56	832,349	60	1,060,137	963	1,195,525	1,099
LAX	67,303,182	0	67,303,182	0	783,433	0	783,433	0	2,038,784	0	2,038,784	0
LGA	25,374,868	0	25,374,868	0	383,325	0	383,325	0	71,149	0	71,149	0
LGB	637,853	0	637,853	0	379,399	0	379,399	0	49,415	0	49,415	0
MCI	15,841,801	28	15,841,801	28	279,970	28	279,970	28	244,619	62	244,619	62
MCO	38,897,365	26	38,897,365	26	540,853	51	540,853	51	545,822	101	545,822	101
MDW	15,857,218	1	25,185,292	61	301,469	1	471,021	58	99,464	371	428,643	1,932
MEM	11,769,213	0	11,769,213	0	388,412	0	388,412	0	2,489,078	0	2,489,078	0

Table 7.17 Maximum possible passengers, aircraft movements and cargo throughput in 2000, Cases 1 and 3 (Continued)

Airport code	Total passengers				Aircraft movements				Cargo (tons)			
	Case 1	% add	Case 3	% add	Case 1	% add	Case 3	% add	Case 1	% add	Case 3	% add
MIA	33,621,273	0	33,621,273	0	517,440	0	517,440	0	1,642,744	0	1,642,744	0
MSP	43,503,104	18	43,503,104	18	616,656	18	616,656	18	1,045,794	183	1,045,794	183
MSY	11,407,888	16	12,596,173	28	184,325	16	203,499	28	164,659	91	204,213	137
OAK	10,963,802	0	10,963,802	0	449,050	0	449,050	0	685,425	0	685,425	0
ONT	6,757,398	0	8,064,476	19	155,501	0	185,542	19	464,164	0	553,947	19
ORD	90,903,872	26	90,903,872	26	1,156,282	27	1,156,282	27	2,437,829	66	2,437,829	66
ORF	3,946,234	29	3,946,234	29	161,378	29	161,378	29	57,061	97	57,061	97
PBI	9,894,942	69	9,894,942	69	324,876	68	324,876	68	434,258	1,971	434,258	1,971
PDX	13,790,115	0	13,790,115	0	314,378	0	314,378	0	282,019	0	282,019	0
PHL	45,168,996	81	47,507,035	91	792,038	64	807,482	67	960,161	72	980,276	75
PHX	36,044,635	0	36,044,635	0	579,816	0	579,816	0	340,352	0	340,352	0
PIT	26,063,445	32	26,063,445	32	550,159	23	550,159	23	180,292	23	180,292	23
PNS	3,769,595	254	3,769,595	254	135,749	15	135,749	15	77,276	1,224	77,276	1,224
PSP	3,991,725	212	5,016,855	292	117,090	41	119,352	44	80,433	61,299	92,445	70,468
SAN	14,868,547	0	14,868,547	0	206,289	0	206,289	0	139,107	0	139,107	0
SBA	776,904	0	776,904	0	167,376	0	167,376	0	2,970	0	2,970	0
SEA	28,408,553	0	28,408,553	0	445,677	0	445,677	0	456,920	0	456,920	0
SFO	64,240,596	56	64,240,596	56	778,647	81	778,647	81	1,707,269	96	1,707,269	96
SJC	13,097,259	0	13,097,259	0	287,072	0	287,072	0	147,929	0	147,929	0
SLC	34,339,104	73	34,339,104	73	614,373	67	614,373	67	432,166	68	432,166	68
SNA	7,772,801	0	7,772,801	0	387,862	0	387,862	0	15,589	0	15,589	0
STL	30,561,387	0	30,561,387	0	481,025	0	481,025	0	130,152	0	130,152	0
SWF	8,144,375	1,428	8,144,375	1,428	138,470	1	138,470	1	156,004	381	156,004	381
TPA	23,090,278	44	23,090,278	44	399,174	44	399,174	44	421,808	309	421,808	309
Total	1,551,380,674	30	1,578,762,310	33	26,008,394	26	26,424,875	28	34,173,774	43	35,253,474	48

Note: Case 3 differs from case 1 in that it drops land area from the set of inputs. Aircraft movements include both delayed and non-delayed flights. % add is the percentage increase from current level of the corresponding output.

Table 7.18 Maximum possible passengers, aircraft movements and cargo throughput in 2001, Cases 1 and 3

Airport code	Total passengers				Aircraft movements				Cargo (tons)			
	Case 1	% add	Case 3	% add	Case 1	% add	Case 3	% add	Case 1	% add	Case 3	% add
ABQ	6,183,606	0	6,302,898	2	242,733	0	247,415	2	72,876	0	87,662	20
ANC	5,107,311	0	5,107,311	0	284,441	0	284,441	0	1,873,750	0	1,873,750	0
ATL	75,858,500	0	75,858,500	0	890,494	0	890,494	0	739,927	0	739,927	0
BHM	3,012,729	0	3,012,729	0	148,869	0	148,869	0	35,433	0	35,433	0
BOS	38,481,290	59	38,481,290	59	703,723	55	703,723	55	628,306	59	628,306	59
BUR	4,487,335	0	4,711,491	5	159,705	0	167,673	5	32,878	0	47,052	43
BWI	20,369,923	0	20,369,923	0	324,065	0	324,065	0	225,083	0	225,083	0
CLE	17,510,135	47	17,868,321	50	428,372	47	437,059	50	150,411	47	153,488	50
CLT	25,890,177	12	25,890,177	12	514,675	12	514,675	12	292,366	65	292,366	65
CMH	6,680,897	0	6,680,897	0	243,201	0	243,201	0	15,260	0	15,260	0
CVG	22,664,832	31	22,664,832	31	506,019	31	506,019	31	493,936	53	493,936	53
DCA	17,476,832	33	17,707,265	34	321,934	32	326,103	34	132,195	425	155,913	519
DEN	37,043,730	3	37,043,730	3	540,903	12	540,903	12	420,832	17	420,832	17
DFW	88,971,994	61	88,971,994	61	1,243,721	59	1,243,721	59	1,378,600	76	1,378,600	76
DTW	45,266,906	40	45,266,906	40	725,372	39	725,372	39	1,442,812	499	1,442,812	499
EWR	30,558,000	0	30,558,000	0	436,420	0	436,420	0	795,584	0	795,584	0
FLL	18,877,562	15	18,877,562	15	333,261	15	333,261	15	209,287	15	209,287	15
HNL	20,151,936	0	20,151,936	0	327,006	0	327,006	0	337,631	0	337,631	0
HOU	11,240,147	30	12,211,045	41	323,801	30	351,588	41	74,212	1,127	63,929	957
IAD	29,224,387	64	29,224,387	64	495,596	25	495,596	25	414,667	25	414,667	25
IAH	34,803,580	0	34,803,580	0	470,916	0	470,916	0	337,842	0	337,842	0
JAN	1,284,311	0	1,284,311	0	92,402	0	92,402	0	14,634	0	14,634	0
JAX	6,926,081	36	6,926,081	36	183,398	36	183,398	36	82,896	36	82,896	36
JFK	37,470,750	28	37,470,750	28	598,329	105	598,329	105	1,826,652	28	1,826,652	28
LAS	35,338,310	0	36,688,573	4	530,328	7	564,386	14	517,649	547	699,128	773
LAX	61,606,204	0	61,606,204	0	738,114	0	738,114	0	1,774,402	0	1,774,402	0
LGA	21,933,000	0	21,933,000	0	365,716	0	365,716	0	52,148	0	52,148	0
LGB	587,473	0	587,473	0	358,508	0	358,508	0	53,190	0	53,190	0
MCI	14,358,821	19	14,358,821	19	250,145	19	250,145	19	236,252	66	236,252	66
MCO	28,253,061	0	28,253,061	0	315,752	0	315,752	0	223,545	0	223,545	0
MDW	15,681,966	0	18,358,628	17	278,734	0	325,549	17	15,684	0	187,012	1,092
MEM	11,808,247	0	11,808,247	0	394,826	0	394,826	0	2,631,631	0	2,631,631	0

Table 7.18 Maximum possible passengers, aircraft movements and cargo throughput in 2001, Cases 1 and 3 (Continued)

Airport code	Total passengers				Aircraft movements				Cargo (tons)			
	Case 1	% add	Case 3	% add	Case 1	% add	Case 3	% add	Case 1	% add	Case 3	% add
MIA	31,668,450	0	31,668,450	0	471,008	0	471,008	0	1,639,760	0	1,639,760	0
MSP	35,058,695	4	35,211,933	4	520,651	4	522,863	4	353,018	4	354,561	4
MSY	9,567,651	0	10,559,396	10	145,564	0	213,523	47	75,700	0	184,203	143
OAK	11,713,225	0	11,713,225	0	395,653	0	395,653	0	593,634	0	593,634	0
ONT	8,302,839	24	8,782,872	31	191,525	24	202,566	31	519,100	24	549,112	31
ORD	75,694,280	12	75,694,280	12	1,063,376	17	1,063,376	17	1,567,465	21	1,567,465	21
ORF	2,963,223	0	2,963,223	0	119,309	0	119,309	0	28,786	0	28,786	0
PBI	7,388,932	24	7,388,932	24	234,992	24	234,992	24	31,619	53	31,619	53
PDX	12,703,676	0	12,703,676	0	291,117	0	291,117	0	242,967	0	242,967	0
PHL	37,847,971	54	38,352,450	56	699,371	50	708,189	52	826,639	54	837,658	56
PHX	35,439,051	0	35,439,051	0	553,310	0	553,310	0	283,337	0	283,337	0
PIT	22,365,971	12	22,365,971	12	506,271	12	506,271	12	155,931	12	155,931	12
PNS	1,057,150	0	1,057,150	0	116,501	0	116,501	0	4,976	0	4,976	0
PSP	2,025,856	72	2,026,702	73	144,738	72	144,798	72	21,966	23,776	19,408	20,996
SAN	15,184,332	0	15,184,332	0	206,988	0	206,988	0	134,689	0	134,689	0
SBA	725,140	0	725,140	0	160,486	0	160,486	0	2,946	0	2,946	0
SEA	27,036,073	0	27,036,073	0	400,635	0	400,635	0	400,499	0	400,499	0
SFO	50,861,183	47	50,861,183	47	730,017	88	730,017	88	934,037	47	934,037	47
SJC	13,088,997	0	14,043,080	7	255,499	0	273,871	7	143,914	0	514,508	258
SLC	22,911,625	22	22,911,625	22	452,824	22	452,824	22	313,835	45	313,835	45
SNA	7,324,557	0	7,324,557	0	378,903	0	378,903	0	14,849	0	14,849	0
STL	36,378,058	36	36,378,058	36	574,174	21	574,174	21	395,215	223	395,215	223
SWF	1,918,917	376	1,918,917	376	119,598	5	119,598	5	20,924	5	20,924	5
TPA	16,355,131	3	16,355,131	3	268,481	3	268,481	3	217,161	172	217,161	172
Total	1,280,691,015	15	1,289,705,328	16	22,772,468	16	23,015,097	17	26,455,537	24	27,372,929	29

Note: Case 3 differs from case 1 in that it drops land area from the set of inputs. Aircraft movements include both delayed and non-delayed flights. % add is the percentage increase from current level of the corresponding output.

Table 7.19 Maximum possible passengers, aircraft movements and cargo throughput in 2002, Cases 1 and 3

Airport code	Total passengers				Aircraft movements				Cargo (tons)			
	Case 1	% add	Case 3	% add	Case 1	% add	Case 3	% add	Case 1	% add	Case 3	% add
ABQ	6,151,129	0	16,538,636	169	254,874	0	298,929	17	74,460	0	340,854	358
ANC	4,914,539	0	4,914,539	0	277,267	0	277,267	0	1,771,595	0	1,771,595	0
ATL	76,876,128	0	76,876,128	0	889,966	0	889,966	0	734,083	0	734,083	0
BHM	2,810,791	0	2,810,791	0	146,555	0	146,555	0	32,353	0	32,353	0
BOS	35,647,876	57	35,662,137	57	610,900	56	611,140	56	609,352	57	609,596	57
BUR	4,620,683	0	4,620,683	0	162,211	0	162,211	0	39,751	0	39,751	0
BWI	19,012,529	0	19,012,529	0	304,921	0	304,921	0	251,354	0	251,354	0
CLE	17,578,887	68	17,729,702	70	420,585	67	424,159	68	170,482	68	171,945	70
CLT	29,952,090	27	29,952,090	27	576,384	27	576,384	27	280,897	75	280,897	75
CMH	6,741,354	0	6,741,354	0	255,630	0	255,630	0	10,700	0	10,700	0
CVG	37,620,386	81	37,620,386	81	582,466	20	582,466	20	420,995	20	420,995	20
DCA	13,941,695	8	15,055,396	17	252,786	17	251,933	17	131,868	2,150	157,961	2,595
DEN	38,229,992	7	38,229,992	7	558,511	13	558,511	13	506,884	52	506,884	52
DFW	91,816,824	74	91,816,824	74	1,302,154	70	1,302,154	70	1,165,008	74	1,165,008	74
DTW	54,507,100	68	54,507,100	68	815,124	66	815,124	66	764,041	228	764,041	228
EWR	30,258,481	4	32,154,783	10	485,889	20	492,992	22	880,784	4	935,983	10
FLL	23,131,236	36	23,131,236	36	379,747	35	379,747	35	224,076	36	224,076	36
HNL	19,749,905	0	19,749,905	0	323,726	0	323,726	0	414,947	0	414,947	0
HOU	11,577,573	44	11,957,427	49	354,136	44	365,708	49	99,629	1,756	59,656	1,011
IAD	31,569,526	85	31,569,526	85	524,229	41	524,229	41	459,860	42	459,860	42
IAH	51,048,711	51	51,048,711	51	743,794	63	743,794	63	514,101	56	514,101	56
JAN	1,221,138	0	1,221,138	0	82,883	0	82,883	0	13,863	0	13,863	0
JAX	7,432,943	50	7,432,943	50	187,219	50	187,219	50	103,415	50	103,415	50
JFK	40,849,751	36	40,849,751	36	584,615	103	584,615	103	2,168,672	36	2,168,672	36
LAS	42,492,287	21	44,094,440	26	602,418	21	623,900	26	983,493	1,100	621,355	658
LAX	56,223,843	0	56,223,843	0	645,424	0	645,424	0	1,779,855	0	1,779,855	0
LGA	21,986,679	0	21,986,679	0	362,439	0	362,439	0	32,223	0	32,223	0
LGB	1,453,412	0	1,453,412	0	350,603	0	350,603	0	53,356	0	53,356	0
MCI	13,342,966	30	13,342,966	30	248,280	30	248,280	30	257,344	89	257,344	89
MCO	27,674,633	4	27,674,633	4	403,408	39	403,408	39	358,923	81	358,923	81
MDW	17,371,036	0	25,651,538	48	304,304	0	446,523	47	26,309	0	249,193	847
MEM	11,141,594	0	11,141,594	0	398,769	0	398,769	0	3,390,800	0	3,390,800	0

Table 7.19 Maximum possible passengers, aircraft movements and cargo throughput in 2002, Cases 1 and 3 (Continued)

Airport code	Total passengers				Aircraft movements				Cargo (tons)			
	Case 1	% add	Case 3	% add	Case 1	% add	Case 3	% add	Case 1	% add	Case 3	% add
MIA	30,060,241	0	30,060,241	0	446,235	0	446,235	0	1,624,242	0	1,624,242	0
MSP	39,838,014	22	39,838,014	22	605,830	19	605,830	19	383,425	20	383,425	20
MSY	9,251,773	0	9,684,859	5	139,291	0	156,839	13	84,150	0	196,986	134
OAK	13,005,642	0	13,005,642	0	371,988	0	371,988	0	634,643	0	634,643	0
ONT	6,517,050	0	7,579,751	16	149,292	0	171,318	15	496,547	0	569,902	15
ORD	66,565,952	0	66,565,952	0	922,817	0	922,817	0	1,473,980	0	1,473,980	0
ORF	3,579,015	3	3,605,579	4	129,782	3	130,745	4	52,005	58	50,334	53
PBI	8,780,743	60	8,780,743	60	265,888	59	265,888	59	54,643	205	54,643	205
PDX	12,241,975	0	12,241,975	0	276,877	0	276,877	0	245,134	0	245,134	0
PHL	24,799,470	0	40,145,233	62	463,167	0	729,445	57	541,039	0	875,831	62
PHX	35,547,167	0	35,547,167	0	545,771	0	545,771	0	298,945	0	298,945	0
PIT	23,785,515	32	23,785,515	32	559,932	32	559,932	32	184,943	32	184,943	32
PNS	1,345,970	0	1,345,970	0	130,826	0	130,826	0	4,518	0	4,518	0
PSP	1,108,695	0	1,108,695	0	85,243	0	85,243	0	74	0	74	0
SAN	14,931,854	0	14,931,854	0	206,380	0	206,380	0	151,644	0	151,644	0
SBA	728,307	0	728,307	0	159,835	0	159,835	0	2,832	0	2,832	0
SEA	26,690,843	0	26,690,843	0	364,735	0	364,735	0	374,753	0	374,753	0
SFO	55,169,980	75	55,169,980	75	756,932	115	756,932	115	1,034,300	75	1,034,300	75
SJC	14,638,695	32	15,884,555	43	296,477	43	295,878	43	184,570	32	234,260	67
SLC	20,741,521	11	20,741,521	11	452,571	11	452,571	11	297,407	38	297,407	38
SNA	7,903,066	0	7,903,066	0	368,627	0	368,627	0	13,730	0	13,730	0
STL	38,825,764	52	38,825,764	52	604,053	38	604,053	38	352,447	173	352,447	173
SWF	362,017	0	362,017	0	123,642	0	123,642	0	13,257	0	13,257	0
TPA	18,015,387	16	18,015,387	16	283,457	16	283,457	16	268,010	192	268,010	192
Total	1,323,382,375	22	1,365,321,443	26	23,101,862	21	23,637,472	24	27,496,714	24	28,235,881	27

Note: Case 3 differs from case 1 in that it drops land area from the set of inputs. Aircraft movements include both delayed and non-delayed flights. % add is the percentage increase from current level of the corresponding output.

Table 7.20 Maximum possible passengers, aircraft movements and cargo throughput in 2003, Cases 1 and 3

Airport code	Total passengers				Aircraft movements				Cargo (tons)			
	Case 1	% add	Case 3	% add	Case 1	% add	Case 3	% add	Case 1	% add	Case 3	% add
ABQ	6,935,011	15	15,625,565	158	253,241	15	312,946	42	133,954	87	305,789	327
ANC	4,791,431	0	4,791,431	0	277,361	0	277,361	0	2,102,025	0	2,102,025	0
ATL	79,086,792	0	79,086,792	0	911,723	0	911,723	0	798,501	0	798,501	0
BHM	2,672,637	0	2,672,637	0	154,849	0	154,849	0	34,184	0	34,184	0
BOS	35,020,347	54	35,114,859	54	569,476	53	570,992	53	943,554	160	1,001,459	176
BUR	4,729,936	0	4,729,936	0	178,079	0	178,079	0	44,654	0	44,654	0
BWI	20,094,756	0	20,094,756	0	299,469	0	299,469	0	235,576	0	235,576	0
CLE	16,180,712	53	17,281,283	64	394,639	53	421,281	63	272,944	185	458,278	379
CLT	31,635,406	37	31,635,406	37	536,801	21	536,801	21	334,987	139	334,987	139
CMH	6,252,061	0	6,252,061	0	237,979	0	237,979	0	10,766	0	10,766	0
CVG	38,539,652	82	38,539,652	82	576,589	14	576,589	14	449,437	14	449,437	14
DCA	14,214,803	0	14,823,901	4	250,802	0	261,399	4	5,774	0	403,062	6,881
DEN	38,894,115	4	38,894,115	4	541,268	8	541,268	8	884,820	172	884,820	172
DFW	83,244,552	56	83,244,552	56	1,185,676	55	1,185,676	55	1,043,533	56	1,043,533	56
DTW	50,696,543	55	50,696,543	55	756,815	54	756,815	54	710,246	222	710,246	222
EWR	29,431,061	0	29,431,061	0	405,808	0	405,808	0	874,641	0	874,641	0
FLL	24,484,401	36	24,493,287	37	389,706	36	389,845	36	226,674	45	227,763	46
HNL	19,732,556	0	19,732,556	0	319,989	0	319,989	0	421,930	0	421,930	0
HOU	10,193,688	31	11,316,924	45	316,623	30	351,390	45	155,183	2,587	333,060	5,667
IAD	28,154,745	68	28,154,745	68	465,444	39	465,444	39	399,990	40	399,990	40
IAH	54,898,411	61	54,898,411	61	743,930	57	743,930	57	683,510	79	683,510	79
JAN	1,215,093	0	1,215,093	0	79,377	0	79,377	0	10,957	0	10,957	0
JAX	6,970,535	43	6,970,535	43	172,836	43	172,836	43	104,553	48	104,553	48
JFK	40,417,649	27	40,417,649	27	570,852	104	570,852	104	2,071,962	27	2,071,962	27
LAS	54,332,887	50	54,332,887	50	743,556	48	743,556	48	510,720	522	510,720	522
LAX	54,982,838	0	54,982,838	0	622,378	0	622,378	0	1,833,300	0	1,833,300	0
LGA	22,482,770	0	22,482,770	0	374,952	0	374,952	0	28,402	0	28,402	0
LGB	2,875,703	0	5,103,201	77	338,807	0	349,176	3	50,873	0	52,431	3
MCI	13,040,110	34	13,040,110	34	229,168	34	229,168	34	265,216	94	265,216	94
MCO	30,308,286	11	30,308,286	11	380,232	29	380,232	29	860,080	346	860,080	346
MDW	18,426,397	0	27,880,730	51	328,035	0	491,221	50	23,266	0	744,163	3,098
MEM	11,437,307	0	11,437,307	0	402,258	0	402,258	0	3,390,515	0	3,390,515	0

Table 7.20 Maximum possible passengers, aircraft movements and cargo throughput in 2003, Cases 1 and 3 (Continued)

Airport code	Total passengers				Aircraft movements				Cargo (tons)			
	Case 1	% add	Case 3	% add	Case 1	% add	Case 3	% add	Case 1	% add	Case 3	% add
MIA	29,595,618	0	29,595,618	0	417,423	0	417,423	0	1,637,278	0	1,637,278	0
MSP	41,741,976	26	41,741,976	26	595,117	17	595,117	17	370,000	17	370,000	17
MSY	10,542,505	14	11,335,042	22	156,040	14	167,701	22	253,278	213	276,540	242
OAK	13,548,363	0	13,548,363	0	342,871	0	342,871	0	597,383	0	597,383	0
ONT	7,258,006	11	7,945,867	21	162,248	11	177,587	21	574,965	11	629,456	21
ORD	69,508,672	0	69,508,672	0	928,691	0	928,691	0	1,510,746	0	1,510,746	0
ORF	3,849,419	12	3,888,687	13	135,951	12	137,337	13	36,821	14	36,532	13
PBI	10,029,678	67	10,029,678	67	284,004	65	284,004	65	175,200	857	175,200	857
PDX	12,395,938	0	12,395,938	0	267,052	0	267,052	0	239,265	0	239,265	0
PHL	39,631,312	61	39,631,312	61	700,772	57	700,772	57	842,526	61	842,526	61
PHX	37,412,165	0	37,412,165	0	541,771	0	541,771	0	288,350	0	288,350	0
PIT	18,913,688	33	18,913,688	33	478,550	32	478,550	32	294,139	142	294,139	142
PNS	1,361,758	0	1,361,758	0	127,197	0	127,197	0	4,569	0	4,569	0
PSP	1,246,842	0	1,246,842	0	93,068	0	93,068	0	103	0	103	0
SAN	15,260,791	0	15,260,791	0	203,285	0	203,285	0	135,547	0	135,547	0
SBA	752,762	0	752,762	0	152,485	0	152,485	0	2,825	0	2,825	0
SEA	26,755,888	0	26,755,888	0	354,770	0	354,770	0	351,418	0	351,418	0
SFO	52,079,506	78	52,079,506	78	600,665	80	600,665	80	1,682,768	193	1,682,768	193
SJC	10,677,903	0	10,677,903	0	198,082	0	198,082	0	108,622	0	108,622	0
SLC	21,972,152	19	21,972,152	19	476,174	19	476,174	19	402,086	85	402,086	85
SNA	8,535,130	0	8,535,130	0	350,074	0	350,074	0	12,050	0	12,050	0
STL	35,870,254	76	35,870,254	76	568,680	50	568,680	50	299,115	159	299,115	159
SWF	393,530	0	393,530	0	112,284	0	112,284	0	19,024	0	19,024	0
TPA	21,158,079	36	21,158,079	36	317,570	36	317,570	36	649,238	595	649,238	595
Total	1,346,865,126	23	1,371,693,477	25	22,573,542	20	22,908,850	22	30,404,043	35	32,195,292	42

Note: Case 3 differs from case 1 in that it drops land area from the set of inputs. Aircraft movements include both delayed and non-delayed flights. % add is the percentage increase from current level of the corresponding output.

Table 7.21 Luenberger productivity indexes, Cases 1 and 3

Airport code	2000 - 2001		2001 - 2002		2002 - 2003	
	Case 1	Case 3	Case 1	Case 3	Case 1	Case 3
ABQ	0.079	0.136	0.009	0.093	-0.090	-0.079
ANC	0.000	0.000	0.000	0.000	0.000	0.000
ATL	0.310	0.310	0.000	0.000	0.000	0.000
BHM	-0.002	0.006	0.000	0.000	0.029	0.028
BOS	-0.079	-0.078	-0.023	-0.027	-0.029	-0.020
BUR	-0.001	-0.002	0.000	0.079	0.000	0.000
BWI	0.015	0.015	0.096	0.096	0.000	0.000
CLE	-0.127	-0.095	-0.068	-0.090	0.035	0.002
CLT	0.040	0.040	-0.003	-0.003	-0.021	-0.021
CMH	0.000	0.000	0.012	0.012	-0.012	-0.012
CVG	-0.170	-0.170	0.219	0.219	0.042	0.042
DCA	-0.220	-0.216	0.091	0.041	0.060	0.093
DEN	-0.019	-0.019	0.033	0.033	-0.008	-0.008
DFW	0.023	0.023	-0.001	-0.001	0.055	0.055
DTW	0.060	0.060	-0.086	-0.086	-0.052	-0.052
EWR	0.011	0.011	0.124	0.167	0.050	0.023
FLL	0.102	0.074	-0.045	-0.045	0.009	0.021
HNL	0.000	0.000	0.000	0.000	0.000	0.000
HOU	-0.073	0.002	0.001	-0.007	0.007	-0.014
IAD	-0.048	-0.048	-0.064	-0.064	-0.055	-0.055
IAH	0.104	0.104	-0.102	-0.102	-0.032	-0.032
JAN	0.077	0.077	0.026	0.026	0.000	0.000
JAX	0.042	0.042	-0.029	-0.029	-0.029	-0.029
JFK	-0.116	-0.116	0.089	0.089	0.043	0.043
LAS	0.235	0.189	0.017	-0.002	-0.111	-0.036
LAX	0.000	0.000	0.000	0.000	0.000	0.000
LGA	0.475	0.202	0.001	0.030	0.173	0.009
LGB	-0.014	-0.016	0.000	0.000	-0.001	-0.018
MCI	-0.025	-0.025	-0.062	-0.062	-0.072	-0.072
MCO	-0.015	-0.015	-0.009	-0.009	-0.021	-0.021
MDW	-0.002	-0.103	0.000	-0.002	0.000	0.045
MEM	0.000	-0.062	0.000	0.000	0.000	0.000

Table 7.21 Luenberger productivity indexes, Cases 1 and 3 (Continued)

Airport code	2000 - 2001		2001 - 2002		2002 - 2003	
	Case 1	Case 3	Case 1	Case 3	Case 1	Case 3
MIA	0.000	0.000	0.000	0.000	0.000	-0.011
MSP	-0.001	-0.003	-0.030	-0.029	-0.002	-0.002
MSY	-0.012	-0.049	0.046	0.036	-0.068	-0.081
OAK	-0.013	-0.013	0.000	0.000	0.000	0.000
ONT	-0.077	-0.032	0.069	0.043	-0.054	0.008
ORD	0.264	0.555	0.170	0.170	0.134	0.134
ORF	0.162	0.162	-0.017	-0.020	-0.047	-0.049
PBI	-0.078	-0.078	-0.138	-0.138	-0.009	-0.009
PDX	-0.015	-0.015	0.000	0.000	-0.003	-0.003
PHL	0.204	-0.022	0.047	0.016	-0.116	-0.014
PHX	0.265	0.075	0.020	0.019	0.008	0.008
PIT	-0.016	-0.016	-0.066	-0.066	-0.138	-0.138
PNS	0.023	0.023	0.001	0.003	0.002	0.003
PSP	-0.056	-0.027	0.314	0.270	0.000	0.000
SAN	0.000	0.000	0.000	0.000	0.000	0.000
SBA	-0.010	-0.010	-0.002	-0.002	-0.018	-0.021
SEA	-0.026	-0.026	0.000	-0.003	0.000	0.000
SFO	-0.105	-0.105	0.014	0.013	-0.056	-0.056
SJC	0.000	-0.047	-0.158	-0.151	0.019	0.106
SLC	-0.061	-0.061	0.096	0.096	-0.056	-0.056
SNA	0.000	0.000	0.000	0.000	0.000	-0.001
STL	-0.109	-0.109	-0.087	-0.087	-0.171	-0.171
SWF	-0.070	-0.070	0.191	0.191	-0.005	-0.005
TPA	0.066	0.066	-0.015	-0.015	-0.093	-0.093
Average index	0.996	0.009	0.681	0.013	-0.013	-0.010
Number of regress	28	29	19	24	27	29
Number of no change	9	7	15	11	15	12
Number of progress	19	20	22	21	14	15

Note: The negative index indicates regressed productivity. Zero value means that there is no change in the productivity between two years. The positive index indicates productivity growth.

Tables 7.22 and 7.23 show the test results from paired-sample t-test and the two nonparametric tests. The t-statistics in Table 7.22 (0.8926, -0.1367, -0.5812, and 0.5096) indicate that the differences in Luenberger indexes between two cases are not statistically significant. Results from nonparametric tests in Table 7.23 support the same inference. The differences in Luenberger indexes are not statistically significant, although the efficiency scores themselves are statistically different (see results in Tables 7.15 and 7.16). The computation of Luenberger indexes really can conceal the difference in efficiency level and in turn can provide a misleading interpretation.

Table 7.22

Comparisons of Luenberger productivity indexes by paired sample t-test Cases 1 and 3

Paired-sample t-test	Paired differences Cases 1 and 3					t
	Mean	Std. deviation	Std. error mean	95% confidence interval of the difference		
				Lower	Upper	
Pair 1: 2000/01	0.0084	0.0708	0.0094	-0.0105	0.0274	0.8926
Pair 2: 2001/02	-0.0003	0.0205	0.0027	-0.0058	0.0051	-0.1367
Pair 3: 2002/03	-0.0025	0.0331	0.0044	-0.0114	0.0062	-0.5812
Pair 4: 2000 – 03	0.0018	0.0466	0.0036	-0.0052	0.0089	0.5096

Table 7.23

Comparisons of Luenberger productivity indexes by nonparametric paired tests

Nonparametric paired test		Z	Asymptotic significance (2-tailed)
A. Wilcoxon Signed-Rank test	Pair 1: years 2000/01	-0.8168 ^a	0.4140
	Pair 2: years 2001/02	-0.9388 ^a	0.3477
	Pair 3: years 2002/03	-0.4867 ^c	0.6264
	Pair 4: years 2000 - 03	-0.5546 ^a	0.5791
B. Sign test	Pair 1: years 2000/01	-	0.6636 ^b
	Pair 2: years 2001/02	-	0.1892 ^b
	Pair 3: years 2002/03	-	1.0000 ^a
	Pair 4: years 2000 – 03	-1.2598	0.2077

^a Based on positive rank

^b Binomial distribution used

^c Based on negative rank

7.5 Determination of airport productivity

A causal model is developed to explain the variations in the efficiency score. For planning and managing an airport, the model will be very useful for predicting future productivity based on given information. The information is treated as exploratory variables which may include number of passengers per runway, passengers per movement, average delay, percentage of international passengers, etc. The dependent variable is the efficiency score.

The model presented here is for Case 1 (with consideration of delays) which is considered as a more complete assessment of productive efficiency. By the nature of the directional output distance function, the value of efficiency scores can only be in the range of zero to infinity. Because of this special type of limited dependent variable,

simple regression is not an appropriate model. The issue was discussed earlier in chapter 5. Censored Tobit regression is employed. In this case, efficiency score of airport y_i is represented by Equation (7.2)

$$y_i = \begin{cases} \beta x_i + \varepsilon_i & \text{if } y_i > 0 \\ 0 & \text{if } y_i \leq 0 \end{cases} \quad (7.2)$$

y_i is an efficiency score that is observable for values greater than 0 and is censored for values less than or equal to 0. Efficiency scores of all efficient airports are censored at 0, regardless of values of independent variables x_i . β and ε_i are the coefficients and the error term of the Tobit model respectively. Coefficients β can be estimated using Maximum Likelihood (ML) method. ML estimation for the Tobit model involves dividing the observations into two sets. The first set contains uncensored observations. The second set contains censored observations. The log-likelihood function is given in Equation (5.3). Meanwhile the marginal effect with respect to an explanatory variable can be computed using Equation (5.4). To measure the goodness-of-fit, the R^2_{ANOVA} given in Equation (5.5) is computed. LIMDEP version 8.0 (Greene, 2002) is used to estimate the model.

7.6 Factors affecting productive efficiency of U.S. airports

The airport operation is a complex process involving a large number of activities. There are many variables that can affect the operational efficiency. Five groups of variables are investigated. The proxy of each group entering the model is essentially based on data availability.

First, *Airport characteristics* are represented here by physical characteristics. These are basically input measures that are used in the directional output distance function, i.e., land area (LAND), number of runways (RW) and runway area (RWA). These inputs certainly play a major role in accommodating traffic. However, one should be aware that having more of these inputs does not necessarily mean more outputs.

Second, *Airport services* are mainly represented by outputs of airport operations which consist of number of aircraft movements (AIR), passengers (PAX) and cargo throughput (CARGO). One would expect that more services contribute to higher efficiency. However, this is not necessarily true since efficiency takes into account both inputs and outputs. Accordingly, another group of variables is introduced, i.e., level of utilization.

Third, *Level of utilization* may be a better determinant of operational efficiency since it takes into accounts both input and output measures. This case study considers many ratio variables, such as non-delayed flights/land area, non-delayed flights/ /runway, non-delayed flights/ runway acreage area, annual total passengers/land area, annual total passengers/number of runways, annual total passengers/runway acreage area, annual cargo throughput/runway acreage area etc. Intuitively, higher values of these ratios should result in more efficient operation.

Fourth, *Market characteristics* include target market (e.g., passengers, aircraft operation, cargo, general aviation and military service), market share, market dominance, market focus (e.g., domestic, international, tourist, business passengers), whether the airport is an airport in a multiple airport system, whether the airport is a hub airport

according to FAA definition, and irregularity of time periods. An attempt was made to collect these variables as much as possible. After all, six variables are entered in the estimation. These include the percentage of international passengers, percentage of general aviation, whether the airport is an airport in MAS, whether the airport is any kind of FAA hub (i.e., large, medium, small, or non-hub), whether the airport dominates in its corresponding MAS, and irregularity of years. In addition, several interaction variables (e.g., whether the airport is an airport in an MAS and also dominates the market etc.) are also tested.

The fifth group of variables is *Service characteristics*. Not only the model considers quantity of airport services, but it also aims to investigate the effects of service quality on the productive efficiency. As pointed out from the results in case study 1, unless quality of services is taken into account, only busy and congested airports will be classified as efficient. This case study takes delays as a proxy to represent service characteristics. Different ratios are computed and entered as exploratory variables. These include percentage of delayed flights, delayed-flights per runway, average delay per passenger and average delay per movement. It is expected that the lower values of these ratios should indicate the higher productive efficiency. In other words, the sign of the coefficients should be positive.

Note that ownership/management characteristic, which is one significant variable in case study 1, is not considered here because there is no difference across airports in the dataset. Every airport, except Stewart International (SWF) is publicly owned and

operated. The inclusion of a dummy variable to represent private ownership does not give the meaningful results.

The model is estimated from the pooled 4-year data (i.e., the years 2000 – 2003). Airports with incomplete independent variables are taken out. Totally, there are 211 complete observations or 13 samples shorter than the full sample size of 224 (i.e., 56 airports x 4 years). Several models consisting of different combinations of exploratory variable were estimated. Table 7.24 shows final model estimation results. It has nine independent variables, including the constant. Other variables are dropped off for reasons such as high correlation among themselves, being insignificant or having illogical sign. Recall that the lower efficiency score is desirable because it indicates that an airport is more efficient. As a result, a negative sign of the three utilization ratio variables in the model, i.e., non-delayed flights per land area (-0.1451×10^{-2}), non-delayed-flights per runway area (-0.5986×10^{-4}) and cargo throughput per runway area (-0.7212×10^{-4}) contribute to higher productive efficiency. They are statistically significant at above the 95% confidence level. The marginal effects in the last column indicate changes in efficiency scores with respect to the changes in the corresponding exploratory variables. For instance, an increment of one non-delayed flight per acre of runway would result in an airport becoming more efficient by -0.2917×10^{-4} units.

Table 7.24 Censored Tobit regression model estimation results

Variables	Proposed model $R^2_{ANOVA} = 1.3106$	
	Coefficient	Marginal
Constant	0.6167** (6.950)	0.3006** (6.276)
% International Passengers	0.0104** (3.646)	0.0051** (3.796)
Non-delayed flights/Land area	-0.1451×10^{-2} ** (-4.612)	-0.0707×10^{-2} ** (-4.672)
Non-delayed flights/Runway area	-0.5986×10^{-4} ** (-2.156)	-0.2917×10^{-4} ** (-2.178)
Cargo/ Runway area	-0.7212×10^{-4} ** (-5.411)	-0.3515×10^{-4} ** (-6.250)
Delay/Passenger	0.1033×10^{-4} ** (4.896)	0.0503×10^{-4} ** (5.105)
Y2001	-0.1724** (-2.730)	-0.0840** (-2.703)
Y2002	-0.1200* (-1.893)	-0.0585* (-1.890)
Y2003	-0.1171* (-1.857)	-0.0571* (-1.857)
Number of observations = 211 Log Likelihood function = -65.8723		

Note:

Dependent variable = Efficiency score

Y2001 = 1 if compute performance score in year 2001, otherwise = 0

Y2002 = 1 if compute performance score in year 2002, otherwise = 0

Y2003 = 1 if compute performance score in year 2003, otherwise = 0

** Estimated coefficient is significant at the 0.05 level (one-tailed)

* Estimated coefficient is significant at the 0.10 level (one-tailed)

Percentage of international passengers (coefficient = 0.0104) is positively associated with the efficiency score. The higher proportion of international passengers leads to lower efficiency. This may be well explained by the longer service time of this target market in comparison to domestic passengers. In general an airport uses more

resources to service an international passenger than it does to service a domestic passenger. The marginal effect suggests that for every additional percent of international passenger, an airport would be less efficient by 0.0051 units.

The average delay per passenger (coefficient = 0.1033×10^{-4}) is also positively associated with the efficiency score as expected. It is understandable that the higher delay leads to lower efficiency but this rarely has been quantified in the past. In this model, the estimation of the marginal effect suggests that for every additional minute of average delay per passenger, an airport would become less efficient by 0.0503×10^{-4} units.

In addition to the above mentioned variables, there may be some effects from anomalies in 2001, 2002 and 2003 since these dummy variables are also statistically significant. The negative signs for these years indicate that airports become efficient slightly more easily in comparison to year 2000.

In summary, the case study has assessed the airport productivity of 56 U.S. airports where joint production of desirable and undesirable outputs is taken into consideration. It also compares results with the case that undesirable outputs are ignored as this is the case in previous studies (See Table 2.4 for the list and description). In the last part of the chapter a productivity prediction model was developed using the Censored Tobit Regression. It is found that the increment of factors such as non-delayed flights per land area, non-delayed flights per runway area, and cargo throughput per runway area contribute to the enhancement of productivity. Meanwhile, the higher proportion of international passengers and average delay per passenger tend to reduce the productivity of airport operations. The model captures anomaly effects in the years 2001, 2002 and

2003 by indicating that airports could become efficient slightly more easily than the year 2000, *ceteris paribus*. In the next chapter, the important findings and insights will be summarized. Potential future research extensions are also suggested.

CHAPTER 8

CONCLUSIONS AND FUTURE RESEARCH

8.1 Conclusions from assessing productivity of airports in MASs

Arguing that it may be more useful to analyze productivity of airports operating in a similar market structure, the case study focused on airports in multiple airports systems (MASs). The data set consisted of 72 airports from 25 MASs in North America, South America, Europe and Asia. Data Envelopment Analysis (DEA) technique was used to assess the relative efficiencies of these airports. It was assumed that land area, number of runways, and runway area were the proxies of operational inputs whereas number of annual aircraft movements and passengers were two main target outputs from the operations. The analysis period was 2000 – 2002.

8.1.1 Productivity of airports in MASs

The assessment indicates that there are two groups of efficient or highly productive airports, coined by the busy and the compact. The busy group consists of market leaders in large MASs such as O'Hare International (ORD), Los Angeles International (LAX) and Heathrow/London (LHR). Air traffic statistics (ACI, 2002 – 2004) confirm that they are among the busiest airports in the world. Airports in the compact group are alternative airports with relatively small land area and only have one or two runways. Clearly airports in both groups are classified as efficient airports because of their relatively higher runway utilization. In this respect, larger airport size does not

guarantee high efficiency. An implication from this result is that an airport must be very busy; otherwise it would not be regarded as an efficient airport. This may make good sense as long as such high utilization does not create undesirable congestion and delays.

8.1.2 Underutilized airports

It is very difficult for all airports in an MAS to be highly utilized because total air travel demand must somehow be distributed among airports (Caves and Gosling, 1999; de Neufville, 1995; de Neufville and Odoni, 2003; Pathomsiri and Haghani, 2005; Pathomsiri, Mahmassani and Haghani, 2004). The effort to manage them by either coordinating or regulating air traffic has not been successful in most cases (Caves and Gosling, 1999; Charles River, 2001; de Neufville, 1995; de Neufville and Odoni, 2003). Given that the capital investment in airport business is very lumpy, it is extremely difficult to keep all runways in an MAS busy (New York/New Jersey region may be an exception). Consequently, functional failure is followed. This seems to be the case in this case study.

It is found that some airports such as Montreal-Mirabel (YMX), Glasgow Prestwick International (GLA), Schoenefeld/Berlin (SXF), and Tempelhof/Berlin (THF) are underutilized. In fact, Montreal-Mirabel (YMX) is a case study of an unsuccessful airport in textbooks (Caves and Gosling, 1999; de Neufville, 1995; de Neufville and Odoni, 2003). Schoenefeld/Berlin (SXF), and Tempelhof/Berlin (THF) and Tegel (TXL, another airport in the Berlin MAS) are planned to be consolidated in 2011. Construction is underway (Berlin Brandenburg International, 2005). In this sense, the proposed models in this case study are useful in pointing out over-investment.

8.1.3 Factors affecting productive efficiency of airports in MASs

The case study estimated a Censored Tobit regression model for explaining variations in efficiency scores of airport operations. Five groups of exploratory variables were investigated, i.e., airport characteristics, airport services, level of utilization, market characteristics, and ownership/management characteristics. It was found that factors such as utilization of land area and runway area, passengers per aircraft movement, market dominance and privately-operated management style contribute to the enhancement of productivity. Meanwhile higher proportion of international passengers tends to reduce the productivity. The model also captured anomaly effects in year 2002 (it was observed that an airport could become efficient slightly more easily with the same utilization rate, possibly due to a global drop in air traffic after the September 11 terrorist attacks). Given some planned measures, the model can be used to predict future productivity of an airport and should be very useful as a tool for planning airport business in a competitive market.

8.2 Conclusions from assessing productivity of U.S. airports

The traditional measurement of productive efficiency of airport operations typically focuses on marketable outputs such as throughput of passengers, aircraft movements and cargo. As confirmed by case study 1, the typical results indicate that efficient airports are very busy airports and frequently they are congested. Reduction in so-called “undesirable outputs” such as delays has never been given credit in the assessment although it is a major concern in airport management. Case study 2 aimed at re-assessing productive efficiency of airport operations by considering joint production of desirable and undesirable outputs.

To estimate relative productivity, airports are viewed as similar production units taking three representatives of capital inputs, i.e., land area, number of runways and runway area; then producing three main desirable outputs, i.e., aircraft movements, passengers and cargo throughput. By the nature of airport operation, there are two byproduct outputs, though undesirable, i.e., delayed flights and time delays. The efficient airports are the ones that both achieve relatively high levels of desirable outputs while keeping the undesirable outputs at relatively low levels. Mathematically speaking, the model ought to simultaneously maximize desirable outputs and minimize undesirable outputs. Data Envelopment Analysis (DEA) seems inappropriate since it seeks to maximize *all* outputs simultaneously.

This dissertation proposed to use the nonparametric direction output distance function. The model is a linear programming problem. Solving it can identify a set of airports that form a linear piecewise efficient production frontier. For inefficient airports, it quantifies the levels of inefficiency. In addition, the maximum possible production can also be estimated to understand how much the potential outputs are. Results are beneficial in many management regards such as performance measurement, benchmarking, ranking and policy development.

The approach was applied in case study 2 to assess the productivity of 56 major commercial U.S. airports. A recent panel data from 2000 – 2003 were used. In order to analyze the impact of the inclusion of the undesirable outputs, a model without accounting for delays was also estimated. There are several important findings and

insightful implications as discussed in Chapter 7. This chapter concludes with those discussions.

8.2.1 Productivity of U.S. commercial airports

Among 56 airports, approximately half of them are identified as efficient during 2000 – 2003. These airports include busy ones such as Hartsfield-Jackson Atlanta (ATL), Los Angeles International (LAX), LaGuardia (LGA), Memphis (MEM), Phoenix Sky Harbor International (PHX), San Diego International (SAN), and John Wayne airport (SNA). Other well-known busy airports such as O'Hare International (ORD), Midway International (MDW), Newark Liberty International (EWR), John F. Kennedy International (JFK), Anchorage International (ANC), Miami International (MIA), Seattle Tacoma International (SEA) and Lambert-St. Louis International (STL) though not classified as efficient show very low inefficiency levels.

In addition, the model also identified several other less busy airports as efficient. They include Birmingham International (BHM), Baltimore/Washington International (BWI), Port Columbus International (CMH), and Oakland International (OAK). These airports are credited because they have relatively low delays. The results indicate that there may be a balance between quantity and quality of outputs in the achievement of efficient outcomes; i.e., airports can trade-off utilization levels for reduced flight and time delays. For certain stakeholders, this option may be an optimal strategy. Passengers and shippers receive service with fewer flight delays. The FAA, as the regulator, has less concern over congestion and safety. Meanwhile, airport managers are able to balance

traffic volume with customer satisfaction. By all accounts, the inclusion of undesirable outputs in the analysis appears to provide a fairer assessment of airport efficiency.

In 2003, the overall system (56 airports) has potential to accommodate increases of about 30% (~1,550 million passengers), 26% (~ 26 million movements) and 43% of total passengers, aircraft movements and cargo throughput, respectively. In numbers, these amounts are equivalent to totally 1,550 million passengers, 26 million movements and 34 million tons of cargo. This would make the system operate at the maximum possible production level. The estimated potential outputs vary across airports. For airport planning, the figure provides a good estimation of excess capacity. An airport manager may use this information in planning an airport improvement program.

Finally, it is observed that when there is a major new investment in an airport, its productivity decreases during early years after the construction. This is the case for Detroit Metropolitan Wayne County (DTW) and George Bush Intercontinental (IAH). DTW opened its sixth runway in 2001 whereas IAH finished constructing runway expansion and extension in 2002.

8.2.2 Productivity growth of U.S. commercial airports

During the period 2000 – 2003, the changes in productivity are rather modest in the narrow range of -1.3% to +1.8%. The airport system on the average had productivity gains in two periods during 2000/2001 and 2001/2002 and productivity loss in 2002/2003. Between 2000 and 2001, the overall average rise in efficiency was 1.8 percent; and continued to increase by 1.2 percent in the next period before falling down

slightly 1.3 percent during 2002 – 2003. The slow growth and regress may be associated with the September 11 terrorist attacks which shook aviation industry worldwide and still had effects during the analysis period.

The netted 1.8% productivity gains between 2000 and 2001 are mainly from efficiency change (airports become +8.8% more efficient) which compensates 7.0% productivity loss from technical change (frontier-shift effect). The situation is opposite in 2001/2002 period when overall 1.2% productivity gains mainly resulted from frontier shift (4.7%). Between 2002 and 2003 both efficiency loss (1.2%) and frontier shift (0.1%) collectively contribute to the overall 1.3% productivity loss.

8.2.3 Impact of delays on airport productivity

It is found out that by ignoring undesirable outputs, i.e., delayed flights and time delays, the results are drastically different in many important aspects. First of all, only a handful of airports (i.e., 6 to 7 depends on the year) are classified as efficient. Exclusively, they are very busy airports that include Hartsfield-Jackson Atlanta (ATL), Los Angeles International (LAX), LaGuardia (LGA), Memphis (MEM), Phoenix Sky Harbor International (PHX), San Diego International (SAN), and John Wayne airport (SNA). All other airports are classified as inefficient with different degrees. Unless traffic is not exceptionally dense, the airport will never be identified as efficient. This is because delays are out of the assessment.

Second, the level of inefficiency as reflected through the efficient score is generally much higher. This is proven by several statistical tests. Consequently, airport

performance looks very poorly although it may not be the case from stakeholders' perception. For instance, the results suggest that Boston Logan International (BOS) handled less than 50% of the level that it should have been able to handle. More precisely, it should have handled about 50 million passengers in 2003 (Table 5.8), rather than just 22.79 million (Table 4.1). The level of inefficiency may be overestimated when delays are not taken into the assessment.

Third, the relative ranking of airports may also be distorted. In particular, smaller and less busy airports that are deemed to be inefficient may appear on the efficient frontier when delays are added as undesirable outputs.

Fourth, the estimated maximum possible production may not be reasonable and practical. The results indicate potential increases of traffic from current levels at around 133%, 91%, and 364% as compared to around 23%, 20% and 35% when delays are considered. The discrepancy may be interpreted as amount of output loss due to cleaning up delays or keeping them at relatively low levels. It can also represent the tradeoff that an airport has to bear in exchange for higher quality of service.

Fifth, the computed productivity indexes are statistically different when delays are accounted for. In many cases, the indexes provided opposite inference regarding the productivity growth. This is actually not surprising since the computation of indexes takes different sets of efficient scores; the resulting indexes are not necessarily similar. The point is that it is crucial to use the right efficiency scores so that the indexes will be meaningful. These are deemed to be the ones with account for undesirable output.

In conclusion, the assessment which does not consider joint production of desirable and undesirable byproduct such as delays will give biased measurements of airport productivity. The interpretation of results can be misleading. Any computation afterwards based on unreasonable efficiency scores including productivity indexes can be confusing. It is strongly recommended to take undesirable outputs into consideration since the results seem to be more reasonable and practical.

8.2.4 Selection of input and output measures

Scenario analyses (i.e., with and without delays, with and without land area) provide insights regarding the effects of chosen measures on the sensitivity of productivity. It is true in general that as the number of input and output measures increase, there will be more airports that are deemed efficient. Note however that the increase in number of airports on the efficient frontier was more dramatic when delays were added than when an additional input (land area) was added. This suggests that consideration of undesirable outputs is at least as important as the consideration of additional input in determining productive efficiency of airports. The failure to include undesirable outputs in the assessment of airport productivity could lead to misleading results.

It is concluded here that selection of input, desirable and undesirable outputs should be carefully considered in tandem in order to provide meaningful, yet practical results. Ignoring undesirable outputs (such as delays) could lead to unwise policy choices for managing airports. For example, unless funding agencies or regulators give credit or rewards to airports for keeping delays at low levels, there will be little motivation to

improve quality of service. Instead, airports may prefer to focus on accommodating increasing levels of traffic without considering downside of these services.

8.2.5 Factors affecting productive efficiency of U.S. airports

A Censored Tobit regression model was estimated for explaining the variations in efficiency scores of airport operations. Five groups of exploratory variables were investigated, i.e., airport characteristics, airport services, level of utilization, market characteristics, and service characteristics. It was found that factors such as utilization of land area and runway area contribute to the enhancement of productivity. Meanwhile higher proportion of international passengers and average delay per passenger tend to reduce the productivity. The model also captured anomaly effects in the years 2001, 2002 and 2003 (it was observed that an airport could become efficient slightly more easily with the same utilization rate). Given some planned measures, the model can be used to predict future productivity of an airport and should be very useful as a tool for planning airport business in the U.S. and other geographical regions.

8.3 Suggested future research

This research pioneers the work on the assessment of productivity of airports operating in MASs and when joint production of desirable and undesirable outputs is taken into consideration. It opens up new opportunities for aviation researchers and practitioners to better understand the relation between inputs and outputs of airport operations. There are several potential extensions to this research that could be conducted in the future. Some of them are suggested here.

1) Consideration of comprehensive input and output measures

An attempt may be made to collect other input and output measures and take them into consideration for assessing the productivity of U.S. and international airports. The input measures in this dissertation may be rather limited to the airside operation. In fact, one may want to see how other capital inputs such as number of gates, terminal area, and apron area could impact the productivity of airports. Financial inputs are also important for airport operations. Environmental factors (e.g., population density, accessibility, and market condition) also have significant impact on traffic volume which in turn affects productivity of airport operations.

On the undesirable outputs, although this dissertation considers perhaps the most conceivable undesirable outputs i.e., delays but there are other undesirable outputs that airport stakeholders are also concerned with such as the number of mishandled baggage and accidents. Even delays could be expanded to encompass a wider number of delay causes. Externality such as noise is perhaps the most frequently-cited undesirable byproduct during the airport planning process. With the current technology, there is no way to get rid of them. However, no study has ever taken them into consideration while assessing productive efficiency of airport operation. It will be very interesting to see how externalities could affect the productivity of airports. Future research may include them into the model.

One might argue that unless these inputs and output measures are not accounted for, the performance measures may be misleading. In this line of research extension, a lot of effort and resources are needed to collect the data since there does not seem to be a

consolidated database. As this dissertation showed, different sets of inputs and outputs can lead to very different results. A reasonable question is how to choose a set of input/output measures that yields robust results, yet is meaningful for airport management.

2) Application in the international context

It will be very useful if one can extend the study framework to assess productivity of airports in the global context so that the valuable lessons may be learned from truly efficient airports, rather than benchmark among U.S. airports only. However, comparison of airports across nations is not an easy task. There will be several other factors involved that affect the efficiency of airport operations. For example, differences in organizational structure may provide different levels of control to airport managers. The definition and measurement of inputs and outputs are also an issue since different countries may adopt different approaches. Again, data availability will be a major hurdle.

3) Better understanding of factors affecting productive efficiency

Many studies have focused on assessing productivity, but relatively few paid attention to the development of prediction models. More research effort may be put forth toward the development of casual models for explaining variation in airport productivity. Such models will enable the managers and policy makers to better understand factors that can enhance operational efficiency. In this area, one may want to investigate effects of other variables beyond those considered in this dissertation. For instance, it is interesting to study the effects of the common ownership of airports in an MAS on their

productivity. One might expect a higher efficiency due to strong coordination, but this has never been studied before. There is a lot more room for research in this direction.

4) Application to other transportation modes

It is not an exaggeration to say that transportation activities create undesirable by-products, regardless of modes. Bus, rail, and water-transport systems all create air pollution. Accidents occur every day on highways. Delays are incurred in all transportation modes. The proposed methodology is certainly well-suited for assessing productivity of other transportation modes. Policy makers may want to know performance of transportation services if these undesirable byproducts are considered. Recently, some researchers (mostly from the economics discipline) started looking at productivity of bus transit by considering joint production of desirable measures and pollutants (e.g., NO₂ and CO₂) (Noh and McMullen, 2006). Productivity and efficiency of trucking industry accounting for traffic fatalities is studied by Weber and Weber (2004).

5) Theoretical development

As for DEA, there is much room for further developing the directional output distance function approach to treat certain cases. For example, it may be adapted to deal with categorical input or output measures such as operating conditions (e.g., snow-belt or not, hub or non-hub, existence of noise abatement program). With this model, it is possible to make an analysis closer to a like comparison which in turn provides fairer and more meaningful results for airport management. Furthermore, the model can be

developed to allow for non-radial expansion and contraction for use in the case that policy makers can reveal preference toward individual input and output measures.

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