INTERNAL AND MACROECONOMIC FACTORS THAT AFFECT THE TECHNICAL EFFICIENCY OF AIRPORTS: AN OCEANIA CONTINENT CASE

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DECLARATION

We hereby declare that:

(1) This undergraduate research project is the end result of our own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this research project has been submitted in support of any application for any degree or qualification of this or any other university, or other institutes of learning.

(3) Equal contribution has been made by each group member in completing the research project.

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ABSTRACT

The principal objective of this research is to investigate and measure the efficiency of airports from the view of panel data analysis. We have applies a two-stage analysis methodology to determine the technical efficiency level of the research target and identify the factors that could possibly sway the technical efficiency level.

By using a secondary data for our sample of study, we composed 3 series of data for a total of 10 different airports across 10 years, which is from year 2007 to 2016 in the Oceania continent countries (5 airports from Australia and 5 airports from New Zealand). In addition, our intention on this study is to test the relationship between internal variables (Workload Unit, Percentage of International Traffic, Airport Operating Hours, Airport Ownership Dummy), macroeconomic variables (Airport Hub Dummy, ln Gross Domestic Product (GDP) per capita, City Population, Percentage of International Passenger) and interaction variables (City Population Multiply Workload Unit, ln GDP per Capita Multiply Workload Unit, Airport Hub Dummy Multiply Workload Unit, Percentage of International Passenger Multiply Workload Unit) with technical efficiency.

For the first set of independent variables which are internal variables, FEM is the preferred model. The results concluded that Airport Operating Hours (AOH), Airport Ownership Dummy (OWN), and Workload Unit (WLU) are found to be significant with technical efficiency in model 1. While the second and third set of independent variables which are the macroeconomic variables and interaction variables, REM are the preferred model.

The results concluded that ln GDP per capita (GDP), Airport Hub Dummy (HUB) and city population (CP) has found to be significant in model 2 meanwhile in model 3 GDP per capita multiply Workload Unit (GDPXWLU) and Airport Hub Dummy multiply Workload Unit (HUBXWLU) are significant towards the technical efficiency.

CHAPTER 1: INTRODUCTION

1.0 Study Background

Airports are some of the busiest places on earth. As an interchange of transport modes and a system that serves a wide and complex range of needs related to the movements of people and items worldwide (Tovar & Martin-Cejas, 2010), airport terminals need to handle thousands of passengers and baggage from arriving flights as well as departing flights 24 hours a day and seven days a week. The airport operation also consists of the landing and taking off of flights round the clock (Up with Airport Efficiency, 2017).

Recently, there has been a rise in interest on measuring the efficiency and performances of international airports around the world by researchers. Therefore, we would like to know why airport efficiency is considered so important and the possible reasons that lead to researchers' rising interest in the issue. The first reason that leads to researchers' rising interest is the privatization trend that is occurring among international airports throughout the world (Tovar & Martin-Cejas, 2010). The aim of this privatization trend is to ensure that resources allocated to the airport could be utilized effectively and minimize the wastage. Therefore, in order to examine the effects of this privatization wave on the efficiency of the airports, studies and researches are carried out to determine its impact. The involvement of private participation in the management and operation of airports also opens up the need for independent researchers to measure the efficiency of the airports. This is because private airport operators could take advantage of their monopolistic position by providing bad services but yet charging a high price for airport passengers (Perelman, S., & Serebrisky, T., 2012). To eradicate such actions by private airport operators, efficiency analysis is crucial to assess how airports are being operated and the reasonability of the tariffs set by the private operators.

The second reason that leads to researchers' rising interest in the issue is probably due to market liberalization of the worldwide airlines industry. The liberalization of the market had resulted in an increased competition among airliners which increased the demand for airport services throughout the world. This had also placed airports in a much more competitive environment where its efficiency means a lot to its survival (Barros, 2008). Airports start to compete with each other for connecting traffic, and the only way to outshine its competitors is by increasing their efficiency level. As a result, the competition pressure had prompted airports to upgrade their efficiency levels to be on par with its competitors to remain competitive in the industry.

The third reason that leads to researchers’ rising interest in the issue is probably due to the increasing globalization of business and tourism related activities. Global airline traffic have been on the rise since the last decade, and in the recent few years accelerated economic growth had significantly pushed the worldwide demand for air travel where its average annual growth rate is expected at 5.2% from year 1997 to 2015 (Ahn, Y. H., & Min, H., 2014). Along with the increase in demand for airport services, airport operations are also getting more complex which requires an excellent management team that has a wide and diverse array of capabilities to run the organization. Surging increase in service expectation and the need to fulfil national or regional development role also means that airports would be continuously challenged to deliver superior efficiency, service quality, and passenger growth. The ability of an airport to operate at high efficiency represents the capability of the management team which is what helps to differentiate an airport.

The fourth reason that leads to researchers’ rising interest in this issue is due to the actions taken by world governments which specifically identified airports as the key to economic development (Doganis, 1992). Governments consider airports to have a significant impact on a country’s economic development and therefore it is important to evaluate and measure the performance of the airport industry in order to ensure that it is up to level. As such, continuous enhancements are considered to be critical for airport management to address in order to retain efficiency (Tsui, Gilbey & Balli, 2014).

In a nutshell, airport efficiency is important to many aspects of the society especially businesses that depends on better connectivity, airport operators that depends on passenger volume and governments that depends on economic development all of which are tools to building a more prosperous nation. Therefore, it is crucial for this study to be conducted.

1.1 Research Background

Measuring airport efficiency and performance had been a growing interest of researchers since the last two decades (Perelman, S., & Serebrisky, T., 2012). As there are more airlines in the industry competing with one another, airports as well started to compete with each other in order to become hub airports which provoke them to increase their efficiency. The airport role as a hub, the location of the airport, and the economic growth rate of the country in which the airport is located are all related to the operational efficiency of the airport (Ahn, Y. H., & Min, H., 2014). The purpose of an airport is basically a transportation infrastructure which allows aircraft to land and take off from country to country. Every airport has infrastructures such as hangars, control towers, and terminals, while larger airports may have their own fixed-based operator services, air traffic control centres, or airport aprons in order to upgrade their efficiency relative to their rivals. According to Crockatt, M. A. (2000), the role of airports is becoming as important as a seaport in attracting economic development and international investment. The operating revenue plays an important role as the fuel of economic growth.

This study is going to measure the technical efficiency of the airport industry in the Oceania continent with inputs such as operating expenses and the number of runways; and outputs such as operating revenue, air passenger movements and aircraft movements. The data of these inputs and outputs variables used to measure the technical efficiency will be collected from all 10 airports that we had targeted for this study.

After finding out the technical efficiency of airports in the Oceania continent, we would proceed to use the efficiency level as an endogenous variable to be gauge by three different sets of exogenous variable namely Internal, Macroeconomic and Interaction. In the process, we will try to find out the relationship and correlation between the endogenous variable and exogenous variable which could be used to improve the efficiency of the airports. Internal exogenous variables included in this study are the airport operating hours (AOH), airport ownership dummy (OWN), workload unit (WLU), and percentage of international traffic (IT), while the external exogenous variables are the city population (CP), percentage of international passenger (IP), airport hub dummy (HUB), ln GDP per capita (GDP). The interaction variables consist of City Population multiply Workload Unit (CP*WLU), ln GDP per capita multiply Workload Unit (GDP*WLU), airport hub dummy multiply Workload Unit (HUB*WLU), and percentage of international passenger multiply Workload Unit (IP*WLU).

Internal factors controllable by a firm could change the efficiency level of an airport. For instance, the airport operating hours (AOH) could directly affect the air passenger movements and aircraft movements. This is proven in Örkcü et al.'s, (2016) journal where the variable is found to be significant in affecting airport efficiency. Airports that operate 24 hours are able to receive more passengers and aircrafts while increasing the operating expenses of late night staffers which influences the inputs and outputs of efficiency measurement. Besides that, the airport ownership dummy (OWN) could also affect the efficiency level of airports. Previous study conducted by Scotti et al. (2012) shows that the airport ownership status is significant in affecting an airport's efficiency score. Government or quasi government owned airports could receive tax incentives or subsidies from the government that might reduce the operating expenses while increasing the operating revenue which influences the inputs and outputs of efficiency measurement. Furthermore, workload unit (WLU) of an airport which is calculated by summing up the number of air passengers and every 100kg of cargo handled could also affect the efficiency level of airports. Tsekeris (2011) had concluded in its study that the WLU is sufficiently significant to affect an airport's efficiency level; therefore a higher workload unit indicates that an airport is capable of handling a larger number of passengers as well as freight cargo which influences the output of the efficiency measurement, thus affecting the efficiency level. Lastly, citing a journal from Oum et al. (2006) and Ulku (2015) the percentage of international traffic (IT) is also proven to be significant in affecting the efficiency level of airports. Compared to domestic passengers, international passengers require more airport infrastructure and facilities to be served such as immigration counters, duty free shops, longer airport runways, etc. The comparatively complicated facilities, infrastructure and complexity needed to serve international passengers will influence the inputs and outputs of the efficiency measurement.

Similar to internal factors, macroeconomic factors uncontrollable by a firm could also influence the efficiency level of an airport. For instance, the city population (CP) that the airport served could directly affect the amount of air passenger movements as well as the aircraft movements. Our anchor paper Tsui, Gilbey & Balli (2014) had found that there is a negative correlation between city population and airport efficiency, although being insignificant, city population is still crucial to measure airport efficiency as correlations varies according to geographical location. Cities with a larger population are deemed to have a greater demand of air travel in terms of passenger numbers, which influences the air passenger movements and aircrafts movements that will serve the demand, this influences the outputs of the efficiency measurement. Besides that, the percentage of international passenger could also affect the efficiency level of airports. Past studies such as Kan (2014), Marques (2014), Bottasso (2012), Pathomsiri (2006) and Oum (2004) had included the variable into their study and found that the percentage of international passengers is significant in affecting airport efficiency. The negative coefficient of the variable in the studies implies a higher proportion of international passengers tend to reduce the productivity of an airport. Therefore we could draw a conclusion that the proportion of international passengers of an airport could possibly affect the efficiency of an airport.

Furthermore, the airport hub dummy (HUB) could also affect the efficiency level of airports. Research journal authored by Kan Tsui, Balli, Gilbey & Gow (2014) had found that an airport's hub status is insignificant to determine the airport's efficiency. However, we can still safely assume that airports that act as hubs for airlines gets more traffic under the hub and spoke operation model by most airlines throughout the world due to the variability of geographical characteristics. This increases the air passenger movements as well as aircraft movements which influences the output of the efficiency measurement. The result found by the authors of the journal does not necessarily apply to all airports around the world. Lastly, the ln GDP per capita (GDP) could also affect the efficiency level of airports. The same journal also found the ln GDP per capita to be insignificant to determine the airport efficiency. Due to the difference in research targets, we could still assume that a larger ln GDP per capita signals a better economic environment in Oceania which encourages consumers to spend more on vacation and travel which increases the air passenger movements at the airport as well as aircrafts movements that will need to serve the demand which influences the output of the efficiency measurement.

Similar to both internal and macroeconomic variables, interaction variables that are used to find out the combined effects of internal and macroeconomic variables by multiplying both variables together is also capable of influencing the efficiency level of an airport. For instance, previous researchers such as Oum, Yan & Yu (2008), Randrianarisoa, Bolduc, Yap, Oum & Yan (2015), and Zhao, Yap & Oum (2014) had applied a similar variety of variables in their research journals which also involves the combined effects of internal and macroeconomic variables. The research done by previous researchers as mentioned above had also inspired us to make a similar move to determine the combine effects of internal and macroeconomic variables on the technical efficiency of our research targets which are airports in the Oceania continent.

1.2 Problem Statement

With the market liberalization of commercial airliners and the globalization of business, commerce, trade, and travel, the demand of air travel had achieved records highs every year since the last two decades (Perelman, S., & Serebrisky, T., 2012). Besides that, the airport had also assumed important roles that represent the country's image and reputation. Its growing importance had also helped airports to gain equal status as seaports in some nations that are tasked to attract foreign investments and create jobs. However, recent discovery had revealed some of the many issues that plague the airports of the Oceania continent.

On May 2017, news regarding major airport delays due to a faulty passport system in Australia and New Zealand (The Guardian, 2017) which accounts for 95% of the continent's air passengers (World Bank, 2015) broke out in the media changes the public perception about the efficiency of airports in the these two countries. This had also sparked our interest in this topic, with an aim to clarify the public's perception as well as to find out the efficiency track record of airports in the continent to determine whether the major delay would be an one off incident or vice versa.

Furthermore, the Commonwealth Games that would be organized on 2018 in Gold Coast City, a suburban area one hour away from Brisbane, Australia also marks a challenge for the airport industry in the continent. Aircraft movements and passengers handled are expected to rise due to the games and it is crucial for the authorities to know the past efficiency level for the airports and the ways to improve it in order to cope with the expected crowd that would visit the country.

Regular tourist and business visitors to the continent had also been rising constantly since year 2000 at an average of 5% a year. Tourism Research Australia (2016) had estimated that the inbound international arrivals of passengers to Australia will increase by 5.9% from 8.3 million to 8.8 million visitors in 2017-2018, and further increase to 12.3 million in 2024. On the other hand, according to statistics acquired from New Zealand's Ministry of Business, Innovation and Employment (2016), the country is estimated to receive an average annual growth of 4.8% starting from 2016 in international arrivals which will reach a total number of 4.86 million by 2023. With a steady rise of international visitors to the continent, there is an urgent need to gauge the technical efficiency of airport infrastructures in the continent to find out whether they are operating at its maximum efficiency or there are inefficiencies that could be further improve. Regional governments might need to upgrade their respective airport infrastructure to handle the ballooning amount of passengers if they were already operating at their maximum efficiency.

Moreover, this study is conducted to know how the efficiency of airports in the Oceania continent perform after the 2014 mining bust in Australia caused by the fall in iron ore and coal prices Lorkin (2017) as well as the 2015 dairy price slump in New Zealand, The Treasury and New Zealand (2017) which accounts for 40% of the country's export. We are keen to find out how do these two incidents that affect Australia and New Zealand's GDP per capita changes the efficiency of the airport industry.

Besides that, through this study we would also like to validate the concept that is widely held by most of the public which is governments or government own companies are inefficient due to bureaucracy and red tape. From the data about the airports that is collected, we found that there are three airports that has yet to be privatized and still remains the asset of regional governments. Hence, we are eager to find out does the government owned status of the airports affect its efficiency.

Lastly, the problem that most of the airports in the Oceania continent is currently facing are airport congestion. The increasing number of flights and passengers that airports needs to handle every day had resulted it to have limited resilience, especially during bad weather where flights need to be diverted or delayed which brings inconvenience not only to the passenger but also losses to the airports. (A mixed bag of opportunities and challenges for airports., n.d.). Therefore, the number and the length of the runway needs to be taken into consideration as it may provide a sign of airport size, and it also can be treated as a proxy of capital investment of an airport for handling aircraft traffic movements. (Tsui, W. H. K., Gilbey, A., & Balli, H. O., 2014).

There are not many research conducted to identify the technical efficiencies of the airports. Therefore, in the interest of this, we have conducted this research to study the factors that affect the technical efficiency and performance of Oceania airports by providing newer datasets, time frame, and better variables.

1.3 Research Question

To fulfil our research objectives that would be listed below, the following questions are raised.

i. What is the technical efficiency level of airports in the Oceania continent?
ii. Do internal factors affect technical efficiency of airports in Oceania continent?
iii. Do macroeconomics factors affect technical efficiency of airports in Oceania continent?
iv. Do macroeconomic factors affect the interaction variable that will then influence the technical efficiency of airports in Oceania continent?

1.4 Research Objective

The aim of this research is to investigate the efficiency and total productivity changes in Oceania continent's airports by using the Stochastic Frontier Analysis (SFA) approach with data spanning from year 2007 to year 2016. In this research, there are seventeen (17) independent variables in total that is used in two stages separately to derive airport efficiency.. The seventeen (17) independent variables comprises of two (2) input variables (operating expenses and number of runways), three (3) output variables (operating revenue, air passenger movements and aircraft movements), four (4) internal factors (airport operating hours, airport ownership dummy, workload unit, and percentage of international traffic), four (4) external factors (city population, percentage of international passenger, airport hub dummy, and ln GDP per capita) and four (4) interaction factors (city population multiply workload unit, percentage of international passenger multiply workload unit, airport hub multiply workload unit, and ln GDP per capita multiply workload unit).

1.4.1 General Objective

The purpose of this research is to measure the technical efficiencies of the 10 airports in Australia and New Zealand and determine the factors that affect them from year 2007 to year 2016.

1.4.2. Specific Objectives

i. To identify the technical efficiency level of airports in the Oceania continent with suitable selection of inputs and outputs variable.
ii. To investigate the relationship between internal variables and technical efficiency level of airports in Oceania continent.
iii. To investigate the relationship between macroeconomic variables and technical efficiency level of airports in Oceania continent.
iv. To investigate the relationship between macroeconomic variables and the interaction variables and its possibility of influencing the technical efficiency level of airports in Oceania continent.

1.5 Significance of Study

The main significance of this study is to provide a continuous and comparable data on the efficiency of major airports for 10 years from 2007 to 2016 in the Oceania continent. Previous studies had only focused on short term data or older data (Tsui, Gilbey & Balli, 2014; Kan Tsui, Balli, Gilbey & Gow, 2014) that could no longer explain the current efficiency trend in the airport industry. Besides the time period, the lack of studies being conducted to gauge the technical efficiency of airports for the Oceania continent as a whole. Past studies had usually singled out an Oceania country or picked a few major airports of the continent to be compared with the entire Asia Pacific region.

Furthermore, this study will also find out the relationship and correlation between the technical efficiencies of the airports in Oceania and the independent variables that might affect it. Unlike the current journals that only use four independent variables; this study uses a wider array of twelve independent variables which is classified as internal, macroeconomic and interactional factors. We would like to establish links and connections between both variables that might help to explain the efficiency of airports in Oceania. The analysis that we have done also helps to identify the significant variables in all internal, macroeconomic and interaction models so that specific actions could be taken to address specific issues that has been highlighted to be significant in improving the airport’s efficiency without wasting resources on efforts that does not help.

This study would likely benefit airport operators and governments in the Oceania continent as the study would disclose the technical efficiency values of all the 10 airports selected in the continent which would reveal its performance as well as the variables that are significant in affecting its efficiency. Airport operators could improve their efficiency by properly addressing internal factors that has been proven in the study to be significant, while governments could improve the efficiency of airports by addressing the macroeconomic variables instead. Other than the airport operators and governments in the Oceania continent, airport operators, governments or city planners in other parts of the world could also refer to this study as a benchmark when they are planning for their own airports.

In this study, we had also included interaction variables that are not found in many previous journals that we have referred to. The inclusion of the interaction variables is important to provide a more comprehensive overview of the combined effects between internal and macroeconomics variable on the technical efficiency of the airports in the Oceania continent. Therefore, it is one of the significance of this study.

With this study, we aim to expand the current vast pool of knowledge by discovering more variables that might explain the efficiency of airports specifically for the Oceania continent. It would also contribute to the studies that had been conducted by previous researchers on the continent given the limited amount of literature discovered.

Lastly, this study to find out the relationship and correlation between technical efficiency of airports in the Oceania continent and eight independent variables serves as a tool for policymakers in the continent to have a clearer understanding on the efficiency of their nation’s key transport infrastructure. The larger amount of independent variables being tested allows policymakers to have a better overview on what affects the efficiency of airports in the continent. This allows limited resources to be directed more accurately which only targets on variables that needs to be further improve to benefit the overall technical efficiency of airports.

1.6 Chapter Layout

This study will consist of a total of five chapters. The first chapter is the research overview which will contain a brief introduction about the study along with the underlying background of the studied area. It would also contain the problems that we face, question that we tried to answer, objectives that we tried to achieve and significance that we tried to create by conducting this study. Moving on with the second chapter, we would conduct a literature review on previous studies where we will find out what had past researchers on this topic had discovered and identify the gaps that had not been studied. In the third chapter, we will outline the data sources, research methodologies, and empirical testing methods used in our study. The outcome from this chapter would then be discussed further in the following chapter. The fourth chapter consist the data analysis where all outcomes obtained from the previous chapter will be broken down, analysed, and reported accordingly. Finally, the fifth chapter contains the discussion of the reported outcome in chapter four. Recommendations and policy implications will be given to policy makers and future researchers in this chapter and conclusions of the entire study would also be drawn and summarize.

1.7 Chapter Summary

This chapter provides a brief overview of our research by starting off with an explanation of the contribution of increasing airport efficiency to the world as an introduction. In the introduction, it also explains the current issues and challenges faced by airports while trying to increase their efficiency as well as other general news that relates to airport efficiency.

Besides that, it also contains a subchapter titled ‘Research Background’ where all necessary background information such as the definition of airport efficiency, current issues faced in airports in the Oceania continent, and the overall relationships of independent variables with airport efficiency is included. It helps readers to have a brief understanding about the topic before the research dives deeper into the details.

A subchapter titled ‘Problem Statement’ is also included where the general problems faced while trying to increase the efficiency of airports are discussed. Issues related to the independent variables that influence the airport efficiency are also explored in detail. ‘Research Questions’ and ‘Research Objectives’ are also part of this chapter where we will identify the questions that this study is trying to answer as well as the objectives that this study is trying to achieve.

The following subchapter would then be ‘Significance of Study’ where it discussed the importance and the possible impact brought by this study. It also stated the contributions that this study would make towards the vast pool of knowledge.

Finally, a ‘Chapter Layout’ wraps up the whole chapter where it would briefly explain about what the study contains in the next four upcoming chapters.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

As a continuation from the first chapter, the second chapter of this final year project would review some of the literatures that had been published by worldwide researchers to support our own study on this issue. To begin with, the first part of this chapter would provide a brief outline on the conceptual and theoretical framework of our study as well as previous literatures that had applied similar techniques in their studies. Moving on, the second part of this chapter would then justify the use of efficiency score as a dependent variable as well as provide past literatures that implemented similar dependent variable to support our claim. In the same part, there would also be sub-sections on the inputs and outputs that help us to derive the efficiency score and past literatures that supported them. Then, in the third part of this chapter we would discuss the independent variables that we had chosen to use in this study. In our case, the independent variables are further classified into internal and external variables which would be further discussed later. Lastly, a conclusion would be provided to wrap up the chapter.

2.1 Theoretical/Conceptual Framework

The theoretical framework that we would apply in our study is known as the Two-Stage Approach which is adapted from our anchor journal (Kan Tsui, Gilbey, Balli & Gow, 2014). In this journal, the researcher had investigated New Zealand's airport industry's efficiency using data between year 2010 to 2012. The two-stage approach applied in the anchor journal consists of two related statistical analysis which are Data Envelopment Analysis (DEA) which is used to find out the efficiency scores of the airports and the Simar-Wilson bootstrapping regression analysis which is used to find out the factors that could possibly affect the efficiency scores.

According to researchers Kumbhakar and Lovell (2000), the efficiency theory is all about obtaining maximum output given a set of fixed inputs (output oriented) or to obtain a set of fixed outputs with minimum inputs (input oriented). On the other hand, the Cobb-Douglas Production Function which is also adopted in the linear regression analysis is used to describe the relationship between the inputs and outputs of a production process, specifically how much output could two or more inputs make. The typical examples of input being used by Cobb and Douglas are labour and capital, while the output being total production. The Cobb-Douglas production function is considered as a simplified form of the economy in which production output is determined by the amount of labour participating in the production and the amount of capital invested in the process. Besides that, the Cobb-Douglas production function also adopts a return to scale measurement to examine the changes in output in relation to a proportional change in all inputs. If outputs increases proportionally to the amount of inputs increases, it would be known as constant return to scale; if outputs increases more than the amount of inputs increases, it would be known as increasing return to scale; and lastly, if outputs increases less than the amount of input increases, it would be known as decreasing return to scale. In the production function α and β are the elasticity symbol of output of capital and labour and the combine of both would be equals to 1 (Tan, 2008).

Other researchers had also been using similar methods to measure the efficiency and the affecting factors in multiple different journals. For instance, the efficiency of 21 Asia-Pacific Airports from year 2002 to 2011 is measured using two-stage approach in Kan Tsui, Balli, Gilbey & Gow (2014) while efficiency of 21 airports in Turkey from year 2009 to 2014 is also measured using the similar method in (Örkcü, Balıkçı, Dogan & Genç, 2016). There are also journals such as (Tsekeris, 2011) which measures efficiency of 39 Greece airports in 2007, (Perelman & Serebrisky, 2012) which measures efficiency of 21 Latin America airports from 2000 to 2007, and (Merkert & Mangia, 2014) which measures 35 Italian and 46 Norwegian airports from 2007 to 2009; all using the two-stage approach technique.

However, with sufficient sample sizes that we are able to obtain from the data we collected for this study; we had introduced some variations to the adapted theoretical framework by replacing the DEA with Stochastic Frontier Analysis (SFA). From Hjalmarsson, Kumbhakar & Heshmati (1996), we are able to know that SFA offers a richer specification especially for panel data which we would be using in this study. Furthermore, SFA also allows formal statistical testing of hypothesis and the construction of confidence intervals which could not be done in DEA and would be useful for us to reject irrelevant null hypotheses in the tests. The shift from DEA to SFA in the two-stage approach applied in our study compared to previous studies would be an attempt by us to address a gap in this field of study which lacks sufficient literature support.

With reference to the theoretical framework of our anchor journal and the necessary variations made, we have created our model based on the case of Oceania airports from year 2007 to 2016 as follows:

First Stage (SFA)

	Input	Output
Efficiency Scores =	Operating Expenses	Operating Revenue
	Number of Runways	Air Passenger Movements
		Aircraft Movements

The inputs and outputs will be used to generate the efficiency scores.

Second Stage (Linear Regression Analysis)

The dependent variable would be the efficiency scores that we would obtain in the first stage, and the independent variables such as Airport Operating Hours (AOT), Airport Ownership Dummy (AOD), Workload Unit (WLU), Percentage of International Traffic (IT), City Population (CP), Percentage of International Passenger (IP), Airport Hub Dummy (AHD), and ln GDP per Capita (GDP) would be used to regress against the efficiency scores to find out the directional causality on airport efficiency.

2.2 Efficiency Scores

According to the Oxford Dictionary (2017), efficiency brings the meaning of achieving maximum productivity with minimum wasted effort or expense. However, academic researchers had further extended efficiencies into different classifications such as economic efficiency, allocative efficiency, technical efficiency and scale efficiency which provide different forms of definition. In our study, we are going to focus on the technical efficiency of the airport industry in Oceania continent.

From Ouattara’s journal (2012), we are able to deduce that technical efficiency is only achieved when a production unit is able to produce the maximum possible output given a fixed input; or the ability to produce a fixed output with the smallest possible quantities of input. The technical efficiency also measures the ability of a production unit to increase production without consuming extra resources and its ability to reduce its use of input to maintain the same level of production. In the context of an airport industry, technical efficiency is used to determine how capable is an airport in handling passengers, aircrafts, retail merchants, assets and their own finances to achieve maximum productivity.

The efficiency score is selected as the dependent variable for this regression analysis due to its relativity as a proxy that helps explains the productivity of an airport. This allows us to identify, gauge, and rank the airports that we study according to their efficiency level.

There had been numerous past literatures that had applied efficiency score as the dependent variable to rank and compare airports locally or internationally. In one study conducted by Scotti, Malighetti, Martini & Volta (2012), efficiency scores are used as a dependent variable to find out the impact of airport competition index, ownership, and degree of dominance of a main airline on Italian airports. Another study conducted by Marques, Simões & Carvalho (2014) had also applied a similar technique to find out the impact of regulation, amount of international passengers, dominance of flight carrier, amount of connecting traffic, aeronautical revenue, gross domestic product (GDP), privatization status, and airport size on 141 international airports. Not only that, a study conducted by Martini, Manello & Scotti (2013) had also further supported the use of efficiency scores as a dependent variable. In the study, Martini, Manello & Scotti finds out the impact of size, airlines, airport ownership, and the mix of aircraft fleet handled by the airport on the efficiency of 33 Italian airports. A research by Coto-Millán, Inglada, Fernández, Inglada-Pérez & Pesquera (2016) had also studied the effect of airport size, existence of low-cost carriers, and the amount of cargo traffic on the efficiency of Spanish airports. Ha, Wan, Yoshida & Zhang (2013) had also used a similar dependent variable to measure the impacts of corporatization, competition, open skies agreements, runway structure, per capita GDP, population and air traffic on 11 airports in China, Japan and South Korea.

With the support of multiple previous academic journals, the choice of efficiency scores as a dependent variable is therefore validated. The selection of the dependent variable also aligns with our aim to find out the factors that would possibly influence the efficiency scores of airports in the Oceania continent.

2.2.1 Efficiency Scores (Input)

To form the efficiency scores that will act as the dependent variable in this study, inputs and outputs are needed to enable the SFA Analysis. In this study, we would incorporate both financial and operational inputs to provide a more comprehensive outcome for the efficiency score.

The first input that we are going to include in the SFA Analysis is the operating expenses. Researchers such as Kan Tsui, Gilbey, Balli & Gow (2014) had made an attempt to include operating expenses as part of an evaluation of the efficiency score in their previous literature used to determine the productivity level of the airport industry in New Zealand. In other studies conducted by Coto-Millán, Inglada, Fernández, Inglada-Pérez & Pesquera (2016) and Coto-Millán et al. (2014), the similar input variable is also applied to find out the efficiency scores of airports in the region of Spain. Not only that, a study conducted by Curi, Gitto

& Mancuso (2011) had also reaffirmed our decision to include operating expenses as an input variable to determine the efficiency score of airports. This is because in the study, Curi, Gitto & Mancuso uses operating expenses as an input variable to detect the efficiency scores of Italian airports. Finally, we are also able to review a piece of literature by Ferreira, Marques & Pedro (2016) which also uses operating expenses as an input to find out the efficiency scores of airports. The targeted geographical locations of this study are 145 airports located in Europe, Asia, and North America.

The second input that we are going to include in the SFA Analysis is the number of runways that an airport has. In a study conducted by Ahn & Min (2014), the number of runways that an airport has is being factored in as an input when the duo tried to determine the efficiency scores of 23 major airports around the world. In another study conducted by Perelman & Serebrisky (2012), the similar input is employed to find out the efficiency scores of airports in the Latin America region. Not only that, a study conducted by Örkcü, Balıkçı, Dogan & Genç (2016) had also reaffirmed our decision to include the number of runways that an airport has as an input variable to determine the efficiency score of airports as the researchers had successfully determined the efficiency scores of Turkish airports using the input variable mentioned. Tsui, Gilbey & Balli (2014) had also used a similar input variable to find out the efficiency scores of New Zealand airports. Finally, we also reviewed a journal by Tsekeris (2011) which also uses the number of runways that an airport has as an input to find out the efficiency scores of airports in Greece.

With a considerable amount of previous academic journals that had used the similar inputs as we do in our study with successful outcomes, we are confident that the inputs that we proposed are logically proven to be valid given the context of an airport industry.

2.2.2 Efficiency Scores (Output)

Aside from the inputs, outputs are also a core to enabling the SFA Analysis that will be the dependent variable of this study. Similar to the inputs, we would also incorporate both financial and operational outputs to provide a more comprehensive outcome for the efficiency score.

The first output that we are going to include in the SFA Analysis is the operating revenue. Researchers such as Tsui, Gilbey & Balli (2014) had made an attempt to include operating revenue as part of an evaluation of the efficiency score in their previous literature used to determine the productivity level of the airport industry in New Zealand. In another study conducted by Tovar & Martín-Cejas (2010), the similar output variable is also applied to find out the efficiency scores of airports in the region of Spain. Not only that, a study conducted by Curi, Gitto & Mancuso (2011) had also reaffirmed our decision to include operating revenue as an output variable to determine the efficiency scores of airports. This is because in the study, Curi, Gitto & Mancuso uses operating revenue as an output variable to detect the efficiency score of Italian airports. Adler, Liebert & Yazhemsky (2013) had also used a similar output variable to find out the efficiency scores of 43 European airports. Finally, we also reviewed a journal by Zou, Kafle, Chang & Park (2015) which also uses operating revenue as an output to find out the efficiency scores of airports. The main locations targeted for this study are the airports situated in the United States.

The second and third output that we are going to include in the SFA Analysis is the amount of air passenger movement and the aircraft movement. In a study conducted by Ahn & Min (2014), the amount of air passenger movement and aircraft movement is being factored in as an output when the duo tried to determine the efficiency scores of 23 major airports around the world. In other studies conducted by Chang, Yu & Chen (2013) and Chow, Fung & Law (2016), the similar output variables is employed to find out the efficiency scores of airports in China. Not only that, a study conducted by Perelman & Serebrisky (2012) had also reaffirmed our decision to include the amount of air passenger movement and the aircraft movement as an output variable to determine the efficiency score of airports as the researchers had successfully determined the efficiency scores of Latin American airports using the output variable mentioned. Finally, we also reviewed a journal by Kan Tsui, Gilbey, Balli & Gow (2014) which also uses the amount of air passenger movements and aircraft movements as an output to find out the efficiency scores of airports in New Zealand.

2.3 Internal Variables

Throughout our research, we found that the internal variable of an airport plays an important role in affecting the airport efficiency. Therefore, we had chosen some airport internal operation such as airport operating hours, airport ownership dummy, workload unit, and the percentage of international traffic for our internal variables. Hence, we are here to find out that whether the internal variable has a significant result towards airport efficiency, each variable are supported by several journals.

2.3.1 Airport Operating Hours

According to Kan Tsui, Gilbey, Balli & Gow (2014), the study implies that it is significant and has a positive relationship between operating hours and airport efficiency, a longer duration of airport operating hours might significantly increase airport's efficiency. However, operating hours has no effect on Adelaide, Narita, and Sydney airport due to their limitation policies. Moreover, the result shows that Turkey airport had positively increase the airport efficiency by 0.135 units due to longer daily operating hours. When there is an increase in efficiency, it allows airports to generate more revenues as the airports can handle more flights and passenger continuously. (Örkcü, H. H., Balıkçı, C., Dogan, M. I., & Genç, A., 2016). Furthermore, according to Kan Tsui, W. H. K., Gilbey, A., & Balli, H. O. (2014), it is also significant between airport operating hours and efficiency. An airport operating hours may determine the air traffic volume, such as the number of air passenger, air cargo volumes, and the traffic movement of aircrafts that pass through the airport. This study had showed that the New Zealand airport efficiency has increase by 0.115 units in every hour.

Besides that, some larger airports who open 24 hours may allow all types of aircraft to land due to high traffic compare to smaller airports who operate 4 hours daily. Smaller airports with low traffic may use operating hours as a strategy to adjust the costs to varying traffic. However, according to Ülkü, T. (2014), the research had performed an analysis to compare the total weekly operating hours of airports and its efficiency. Surprisingly, the analysis shows an insignificant result that the airports with longer operating hours are statistically less efficient, a 13 percent less in efficient to be exact. While smaller size airport may choose to reduce operating hours to increase airport efficiency and operational cost.

2.3.2 Airport Ownership Dummy

According to Marques, R. C., Simões, P., & Carvalho, P. (2015), a dummy variable which is the airport ownership is picked in order to identify whether the influence from privatisation will affect the performance of an airport. The value of 1 represent that the airport is privately owned and managed by a firm, while the value 0 is refer to the airport is owned and managed by public sector. Most of the international airports are usually owned and run by local or national government which considered as public sector, however, airports in Eastern Europe, Asia and Oceania practices privatisation widely. The intentions are either privatising partially or entirely of airports in Western Europe, South America and Africa. It is expected that privatisation will actually have a positive impact on the airport efficiencies. However, there are studies that emphasizes on public sector ownership as it could increase efficiency. Martini, G., Manello, A., & Scotti, D. (2013) believes that if the public local authorities such as local government who has the airport ownership, they will pay more attention to the environment effect that caused by airports such as noise pollution. A dummy variable of value equals to 1 when the public sector has more than 50% of the airport shares, value of 0 otherwise.

According to See, K. F., & Li, F. (2015), European country including United Kingdom has been acknowledged as leading to an overall increase in privatisation. privatisation may lead to an increase in the vulnerability of the industry as the operating margins are narrow. (Perelman and Serebrisky, 2012). The study shows that there are 55 percent of major airports in United Kingdom were owned by private sector, 36% were under mixed ownership, and the rest were owned publicly. Theoretically, privatisation are expected to trigger the efficiency as there are greater market competition and more commercial focus, but there is no assurance that market reformation will benefit final customers and the economy. Privatisation of airport ownership is significant towards airport efficiency as it is largely profit oriented and able to diversify the business with little government control. The coefficients are also significant with Kan Tsui, W. H. K., Gilbey, A., & Balli, H. O. (2014), a privately owned airports resulted more efficient by 0.376 units in New Zealand airports as the profit is maximize through more commercial basis.

2.3.3 Workload Unit

Other than that, the airport size is also used as one of the internal variables, which is measured in the terms of workload unit (WLU). According to Cotton Millan et al (2016) and Barros (2008), airport size is significant to airport efficiency with a positive coefficient, which indicating that larger airport is likely to have higher overall efficiency and scale efficiency as compared to smaller airport. The result shows that airport size is significant to the airport efficiency at the significance level of 1%. Tsekeris (2011) further supported that the size of operation can be attributed to the economies of scale and needed for development of airports by enhancing the scale of operations. In the research, result also shows a positive effect of airport operation size is statistically significant on efficiency at 10%, which largely relates to the increased output of airports sited.

Besides that, Martini, Manello & Scotti (2011) also stated that airport with different size will affect the efficiency and is positively related to the airport efficiency. The positive impact of airport size suggest that larger airport size will have higher achievement on the airport overall efficiency in term of technical and environmental efficiency. Size is significant but it has negative sign which indicating that there are scale economies also only when desirable outputs are taken into account. Lastly, in the research of Marques, Simoes & Carvalho (2014), they found out that high percentages of international passengers will have negative influence on the efficiency of small scale airport and a positive influence on the efficiency of those medium and large scale airport. They suggest that airport should expand their size in order to achieve greater efficiency and also to increase the percentages of international passengers.

2.3.4 Percentage of International Traffic

Lastly, we have included the percentage of international traffic as our fourth internal variable. According to (Örkcü, Balıkçı, Dogan & Genç, 2016), the variable percentage of international traffic is found to be significant factor that explain airport efficiency. They found that that percentage of international traffic is negative related with airport efficiency, indicating that every increase in percentage in international passengers handled by an airport, the airport efficiency reduced by 0.033 units. This is because more sophisticated infrastructures and facilities and larger airport capacity are needed when there is a high percentage of international passengers in order to serve the international traveller, which is a high expenses and the operational will hence become tougher and more complex.

For example, the air passenger traffic in international markets for Spain and Turkey has grew sharply from year 2003 to year 2012. The facilities and infrastructure cannot meet the growing demand. The countries has expanded their airport by building new runways, new terminal and also upgrading their facilities and infrastructure to overcome the capacity limitation which increased their public debt (Ülkü, 2014). Ülkü (2015) further supported that the negative coefficient of the share of international traffic indicates higher share of international traffic has an adverse effect on performance. This is due to more sophisticated infrastructures and operational costs are needed.

In addition, Oum, Adler & Yu (2006) has also proved that the percentage of international traffic has a negative coefficient with the airport efficiency. However, they found that that is it not statistically significant. The cross term with European regional dummy shows statistically significant with negative coefficient but with Asian regional dummy, it is statistically significant but with positive coefficient. This shows that North America and Europe airports are relying heavily on international travellers while in Asian, airports are having more international traffic with higher gross variable factor productivity (VFP). The insignificant relationship also stated in the research of Ha, Wan, Yoshida & Zhang (2013). They found that percentage of international traffic is having insignificant relationship with airport efficiency. They found that the international traffic is improving the airport efficiency in China and Asia which indicating positive relationship between international percentage and airport efficiency. However, they also realised that the percentage of international traffic is negative related to the efficiency of airports in North America and Europe.

2.4 Macroeconomics Variable

Based on the research we had done, it shown that the airport efficiency not only affected by internal variables but also external variables. Therefore, we had selected some of the macroeconomics variables as external variables that will bring impact to the airport efficiency. Here are some of the external variables we had chosen and all the external variable is support by several journals to illustrate whether the external variables has a significant result to the airport efficiency:

I. City population
II. Percentage of International Passenger
III. Airport hub dummy
IV. GDP per capita

2.4.1 City Population

According to Kan Tsui, Balli, Gilbey & Gow (2014) and Merket & Mangia (2012) has shown that it was a significant result between city population and airport efficiency when the costs are take into account for input variables. The sign of the city population is expected to be positively to the airport efficiency because as the larger the amount of the population, the more airport demand can be generated, so it will lead to a higher efficiency of the airport. Furthermore, it is easy for a large airport to increase airport traffic volumes as relative to higher airport demands and larger airport hinterland. Although the evidence from Turkey shown the city population and airport efficiency is not statically significant related, it has a positive effect on airport efficiency. According to Orkcu et al. (2016), airport will be higher efficiency when the airport serve a larger hinterland population compare to a smaller population. Besides, a higher airport efficiency also help the airport to generate more profit as it can generate more demand where there is a lots of passengers. However, according to a research in New Zealand illustrated that the city population could has a negative impact on the efficiency of airport. This is because as the amount of city population increase, the possibility to build up a larger airport infrastructure and capacity is needed to accommodate the amount of city population, thus it will cause the efficiency in the airport become lower (Kan Tsui, Balli, Gilbey & Gow, 2014) and (Merket & Mangia, 2014). For example, the Brescia Airport has the highest city population among the catchment area but its traffic level and performances are very low compare to other airports because of the presence of competition in the market. Therefore, we can conclude that a large overlap catchment area will cause the performance and traffic level of the airport will be lower too.

2.4.2 Percentage of International Passenger

Moreover, percentage of international passenger also is one of the external variable that will directly affect the airport efficiency. The relationship between percentage of international passenger and airport efficiency can be positive or negative and also sometimes will significant and sometimes will not significant it is largely depend on the geographic location of the airport (Tsui et al., 2014; Marques et al., 2014; Bottasso et al., 2012; Pathomsiri, 2006 & Oum & Yu, 2004). Different geographic location will bring different amounts of revenues and costs, thus it will directly influence the efficiency of the airport. According to Tsui et al. (2014) and Pathomsiri (2006) showed a significant result between percentage of international passenger and airport efficiency but it is a negative coefficient. This finding had claimed that in order to attract more international passenger, they need to build a larger airport infrastructure and facilities to serve international passenger compare to domestic passenger. In general more international passenger will cause an airport use more resources and huge amount of costs to serve them and the airport will earn lower profits or loss.

Other than that, another researcher also examine the relationship between percentage of international passenger and airport efficiency by using Variable Factor Productivity (VFP). VFP is an important indicator in this situation because the efficiency level of an airport utilizes the variable inputs at a given level of capital infrastructure and facilities is measure by VFP. Therefore, higher percentage of international passenger is expected to have a lower VFP and the airport efficiency is expected to be lower too (Oum & Yu, 2004). However, several researcher found that the impact of percentage of international passenger on airport efficiency is positive. The sign of the percentage of international passenger is expected to be positive if the airport has a rich historical past or is in a developing country. This is because the possibility of a developing country will have a larger airport is higher compare to least developed country, therefore, there will be a positive influence on the airport efficiency (Marques et al., 2014) and (Bottasso et al., 2012).

2.4.3 Airport Hub Dummy

Besides, we also include airport hub dummy as our external variables because it is use to detect the strategic location of an airport and also to identify the level of flight connectivity network. The majority of studies found that there was a positive effects between airport hub status and airports efficiency but not any significant relationship (Orkcu et al., 2016; Scotti et al., 2012; Tsui et al., 2014 & Wanke, 2012). Based on Tsui et al. (2014), even though hub status and efficiency of an airport was not significant. However, its coefficient can be proved through the airports that serve as an international hub airport which will have more efficiency than the airports serve as non-hub or regional airports. From previous studies (Fung, Wan, Hui & Law, 2008 and Perelman and Serebrisky, 2010) also claimed that international hub airports can improve airport efficiency due to its' size and location advantages which can transport more airport traffic than regional airport. On the other hand, Tsui, Gilbey, & Balli (2014) and Zou et al. (2015) have show that it was a significant result between hub status and airport efficiency. According to Zou et al. (2015), the sign of the hub status is expected to be negatively to the airport efficiency because of the larger size hubs will lead to a higher efficiency of the airport when compare with medium hub airports. Although the estimated result for non-hub airports are statistically insignificant, but the coefficients of non-hub and small airports still show a similar downward effects when compare to large hubs. This supported by Tsui, Gilbey, & Balli (2014) which indicate that international airports were less efficient than non-hub airports or regional airports.

2.4.4 Gross Domestic Product (GDP) per capita

Lastly, gross domestic product (GDP) is a basic indicators used to measure a region country's economic output. It represents the market value and the total dollar value of all final goods and services produced within the borders of a region country over a specific time period. According to Marques et al. (2014), Chi-Lok and Zhang (2009), Randrianarisoa et al. (2015) and Tsui et al. (2014), it was a significant result between GDP and airport efficiency. Report Randrianarisoa et al. (2015) stated that GDP executes more on the time and specific macroeconomic factors in the respective country, for example, productivity shocks. So, airports that operate in the developed countries contribute to a high-level efficiency than the developing and under-developed countries (Randrianarisoa et al., 2015). Tsui et al. (2014) and Ha et al. (2013) stated that In GDP per capital has a positive impact on airport efficiency, indicating that a hinterland which with a strong air travel demand will to bring up the airport's efficiency. This will implement an increase in per capital GDP of a city or country that might increase an airport's efficiency. Besides that, an ambiguous and negative impact on airport efficiency was founded from Marques (2014) and Chi-Lok and Zhang (2009).

Based on Marques (2014), GDP is usually positive correlated with the standard of wealth and living. A higher GDP would generate more flights, so it has positive effect on the performance of airports. It is not only influence by the economy growth that is correlated with the increase of the transportation costs and also others factor like household income which also will affect GDP. However, the result possibly be ambiguous due to even be a poor destinations (historical) also have quite visited but the GDP was identify based on the purchasing power of buyer per capital at region or state. The researcher found that no matter the values of GDP is higher or lower, there will have a positive influence on the efficiency of airports. This confirms the truth of what Chi-Lok and Zhang (2009) reported that in poor regions also might have a positive influence on the efficiency of airports.

2.5 Interaction Variables

Previous researchers such as Oum, Yan & Yu (2008), Randrianarisoa, Bolduc, Yap, Oum & Yan (2015), and Zhao, Yap & Oum (2014) had included interaction variables into their studies on airport efficiency to research on the combined effects of two variables on the technical efficiency of airports. Despite using non-similar variables as the previous researchers had in their studies, we would still adopt the model to provide a more comprehensive approach and perspective on the issue and geographical location that we had chosen to focus on.

As a result, we had formed four interaction variables by interacting all of the macroeconomic variables with Workload Unit (WLU), an internal variable. This causes us to have four new interaction variables as follows:

i) City Population multiply Workload Unit

ii) Percentage of International Passenger multiply Workload Unit

iii) Airport Hub Dummy multiply Workload Unit

iv) ln GDP per Capita multiply Workload Unit

2.6 Chapter Summary

This chapter provides an overall review of past literatures related to our study. Variables are examined in detail and past journals are presented to support the variables that will be used in our study. Throughout the chapter, we did an in-depth review of the dependent variable where we identify suitable inputs (operating expenses, number of runways available in airport) and outputs (operating revenue, air passenger movements, aircraft movements) that could be used to construct the efficiency score. Then, we review the independent variables where we identify suitable internal (airport operating hours, airport ownership dummy, workload unit, percentage of international traffic) and external (city population, percentage of international passenger, airport hub dummy, ln GDP per capita) variables that could possibly influence the efficiency score.

All relationships between independent variables (IV) and dependent variables (DV) in the study in previous journals are identified and its causality determined. This allows us to have a better understanding of the interactions between IV and DV and know what to expect in the following chapter where we will apply statistical methodologies to find out the outcome. This chapter also provides a basic understanding of the theoretical framework known as Two-Stage Analysis which we would apply in this study. The gap from previous literatures is also identified, and our study aims to narrow it down.

CHAPTER 3: METHODOLOGY

3.0 Introduction

In this chapter, we are going to give an insight to the theoretical framework, variables, and econometric models that we would be adopting in our research. First of all, we are going to breakdown our research's theoretical framework into three interrelated parts which we would explain in details later on in the chapter. The first part of the theoretical framework consists of fundamental understanding of two production functions namely Cobb-Douglas and Translog production functions. The second part of the theoretical framework would consist of the benefits of choosing Stochastic Frontier Analysis (SFA) over Data Envelopment Analysis (DEA) as well as some fundamental concepts of SFA which is derived from production functions such as Cobb-Douglas and Translog. In the third part of the theoretical framework, we would introduce the input-output approach which is used by the SFA to gauge the technical and allocative efficiency of the major airports in the Oceania continent.

In line with our theoretical framework, we've generated a few models for our research that would be further discussed in later parts of the chapter. In the first model, we would be using the SFA technique to establish a relationship between the inputs and outputs that we have chosen in order to determine the efficiency of major airports in the Oceania continent. Then, with the efficiency score obtained from the first model, we developed the second and third model where the regression technique is used along with the internal and macroeconomic variables that would act as independent variables in two respective models to gauge how much does these independent variables affect the efficiency level of airports in the Oceania continent.

To enable our research into the research questions that we've raised in Chapter 1, we've collected the data of the variables that we would be using in our models for

10 consecutive years ranging from 2007 to 2016 for all 10 major airports situated on the Oceania continent that we've pinpointed as our research targets.

Also, in the ending of the chapter we would be introducing econometric frameworks such as Fixed Effects Model, Random Effects Model, Pooled Ordinary Least Squares and Panel Unit Root Test to ensure that the estimated outcome from our regression model is not spurious and unbiased.

3.1 Production Function

3.1.1 Cobb-Douglas Production Function

The Cobb Douglas Production Function was first developed by researchers Paul Douglas and Charles Cobb back in 1927. The production function developed by the duo works as an equation that is used to describe the relationship between the inputs and outputs of a production process, specifically how much output could two or more inputs make. The typical examples of input being used by Cobb and Douglas are labour and capital, while the output being total production. The standard form of Cobb-Douglas production function can be denoted as:

$$Y=AL^{\beta}K^{\alpha}$$

Where:
Y= total production (total number of goods produced by a company in year or 365 days)
A= total factor productivity and the utility depreciation in one day
L= labour input (total number of person worked per hour in year or 365 days)
K= capital input (real value of buildings, equipment and machinery)
α and β= the elasticity of output of capital and labour

Besides that, Cobb-Douglas production function could also be treated as either a long run or short run production function. In the short run which symbolizes a shorter time horizon, some of the capital inputs used by the production function needs to be treated as fixed such as building, equipment and machinery. While in the long run which symbolizes a longer time horizon, the capital inputs can be treated as variable (Coelli, 2005).

However, the arguments about the limitations of the Cobb-Douglas production function are also raised by researchers such as (Balistreri, McDaniel & Wong, 2003). Based on our knowledge, we know that the capital-labour measurement used in Cobb-Douglas production function is substitution elasticity, but it is problematic and controversial. Looking at the production function from a structural perspective, we could see that the capital accumulation faces a complex dynamic problem; hence, any estimation based on a static notion of capital input demand are very likely to suffer from misspecification bias.
Despite that, the Cobb Douglas production function is still widely used by researchers in fields of social sciences due to it having convenient and realistic properties.

3.1.2 Translog Production Function

On the other hand, the term Translog (transcendental logarithmic) production function is first proposed by researchers Christiansen, Jorgensen and Lau (1973) back in 1973 in their research to deal with the problems of strong additivity and homogeneity that exist in the Cobb-Douglas and Constant Elasticity of Substitution (CES) production function. The additivity and homogeneity problem that exist in both the Cobb-Douglas and CES production function had resulted in biases when the production functions tries to estimate two or more inputs at a time.

A Translog production function with three inputs could be written in terms of logarithm as follows:

$$\ln(Y)= \ln(A) + \alpha_L \ln(L) + \alpha_K \ln(K) + \alpha_M \ln(M) + b_{LL} \ln^2 (L) + b_{KK} \ln^2 (K) + b_{MM} \ln^2 (M) + b_{LK} \ln(L) \ln(K) + b_{LM} \ln(L) \ln(M) + b_{KM} \ln(K) \ln(M)$$

Where:

A = total factor productivity

L = labour

K = capital

M = materials and supplies

Y = output

However, the very first form of the Translog production function could trace its roots back to year 1967 where researcher Kmenta (1967) presented an approximation of the CES production function with a second order Taylor polynomial. The elasticity of substitution of this approximation is very close to the unitary value, in which is the case of the Cobb-Douglas production function.

The Translog production function is comparatively more general than the Cobb-Douglas and CES production function that it has a flexible functional form that permits the partial elasticity of substitutions between inputs to vary. It also takes into account a number of n inputs that could be expressed in the equation as shown below:

$$lnY = lnA_{\alpha_i,\beta_{ij}} + \sum_{i=1}^{n} \alpha_i \ .lnX_i + \left(\frac{1}{2}\right) .\sum_{i=1}^{n}\sum_{j=1}^{n} \beta_{ij} \ .lnX_i \ .lnX_j$$

Furthermore, based on researcher Pavelescu (2011), one of the main advantages of Translog production function is that it does not imposes rigid conditions such as perfect substitution between production factors or perfect competition on the production factors market. Translog production function is also widely used in econometrics due to it is linear in parameters where ordinary least squares (OLS) is applicable.

3.2 Input-Output Oriented Approach

The input-output oriented approach is widely used to determine the efficiency of an organization. However, before trying to explain the input-output oriented approach, one should first understand the theory of efficiency. According to researchers Kumbhakar and Lovell (2000), efficiency is all about obtaining maximum output given a set of fixed inputs (output oriented) or to obtain a set of fixed outputs with minimum inputs (input oriented).

Based on Farrell's (1957) research the researcher proposed that in the field of economics, organization's efficiency is mainly measured in terms of economic efficiency which is made up of two different efficiency elements where the first efficiency element being the technical efficiency (TE) and the second efficiency element being the allocative efficiency (AE) as depicted in the equation below.

$$\boxed{\text{Economic efficiency} = \text{Technical Efficiency} + \text{Allocative Efficiency}}$$

3.2.1 Technical Efficiency (TE)

From Ouattara's (2012) research journal we know that, technical efficiency is a degree of measure of an organization to find out whether it is able to increase its production without consuming more resources or reduce the use of inputs without compromising the current level of production. Other researchers such as Kokkinou (2009) had also tried to explain technical efficiency using a production frontier which is constructed by calculating the maximum output that is attainable given a fixed set of inputs. The production frontier defines technical efficiency in a way where a minimum set of inputs is able to produce a given number of output or a maximum output that is able to produce by a given number of inputs.

If the organization produces anything less than what it could feasibly produce, it is deemed to be inefficient and its production point plotted on a graph would lie below the pre calculated frontier. In other words, any deviations from the pre calculated production frontier would symbolize a technical inefficiency in the organization. The equation to calculate technical efficiency could be written as follow:

$$TE_{it} = \frac{observed\ output}{potential\ maximum\ output}$$

$$= \frac{f(x_{it}\beta) \times \exp(v_{it}) \times \exp(-u_{it})}{\exp(x_{it}\beta)}$$

$$= \exp(-u_{it}), 0 \leq TE_{it} \leq 1$$

Where:

$f(x_{it}\beta)$ = Production frontier
$\exp(v_{it})$ = Noise
$\exp(-u_{it})$ = Inefficiency
$\exp(x_{it}\beta)$ = Potential maximum output

As depicted in the equation, technical efficiency could only fall between zero and one, with one symbolizing full technical efficiency and zero symbolizing complete technical inefficiency.

3.2.2 Allocative Efficiency (AE)

According to researcher Ouattara (2012), allocative efficiency is related to the input utilization by organizations according to current prices in the market. An organization is considered to have allocative efficiency if the cost incurred by the organization to produce outputs is similar to the minimum cost of outputs quantity production. In a research journal written by Rodríguez-Álvarez, Tovar & Trujillo (2007), the researchers mentioned that there are two methods to calculate the allocative efficiency of an organization, namely error components approach and parametric approach. However, in this study we would only be discussing the parametric approach which involves a production frontier. The equation to calculate allocative efficiency using the parametric approach could be written as follow:

$$Market\ Price\ Ratios = Shadow\ Price\ Ratio$$

$$\frac{\delta D(y,x,K,DT)/\delta x_i}{\delta D(y,x,K,DT)/\delta x_j} = \frac{w_i^s}{w_j^s}$$

Where:

D(y,x,K,DT) = Short-run input distance function
y = Output vector
x = Variable input vector
K = Quasi-fixed input
DT = Time year dummy used to control for neutral technical change
w^s = Shadow price vector

From the equation, if the allocative efficiency assumption is satisfied, the shadow price ratio would coincide with the market price ratios. However, if there is allocative inefficiency both price ratios would differ. For this research, we would only use technical efficiency as our main indication to measure the efficiency of a 10 airports in the Oceania continent.

3.2.3 Justification for Using only Technical Efficiency (TE)

The justification for us using only technical efficiency instead of both technical efficiency and allocative efficiency in our study is provided by one of our anchor journals which is written by researcher Barros (2008). In this journal, the researcher had used only technical efficiency as the sole measurement for airport efficiency in the United Kingdom. Furthermore, researchers Kumaran, Abdullah & Hussin (2015) and Abdullah & Kumaran (2015) which also uses similar technique had also provided further justification for the method. Therefore, with such precedence; we would be adopting a similar technique in our study when measuring airport efficiency in the Oceania continent.

Besides the justification provided by one of our anchor journals, the rationale behind the adoption of only technical efficiency to measure airport efficiency in the Oceania continent is driven by technical efficiency's focus on organization productivity in order to determine competitiveness instead of allocative efficiency's cost minimization. Our study wanted to find out the ability for airports in the Oceania continent to cope with the rising demand and its resilience to factors surrounding its operation. Therefore, technical efficiency would be a more suitable measurement compared to allocative efficiency in determining such abilities by allowing the inclusion of operation factors instead of just financial factors of the airports.

3.2.4 Parametric or Non Parametric Efficiency Measurement

From the above, the measurement of efficiency in an organization mostly requires the construction of production frontiers. According to Jarzebowski (2013), there are two different approaches to measure the efficiency which are the parametric method that uses the stochastic frontier analysis (SFA) and the non-parametric method that uses the data envelopment analysis (DEA).

3.2.4.1 Stochastic Frontier Analysis (SFA)

The parametric method that uses SFA to measure efficiency is first proposed by researchers Aigner, Lovell, and Schmidt (1977) back in year 1977. From Jarzebowski's (2013) journal we know that, SFA is developed based on production function which requires assuming a specific functional form that determines the inputs and outputs relation a priori. It could also be used to estimate a parametric frontier of the best plausible practices given a fixed cost function or profit function. Both Cobb-Douglas production function and Translog production function could be utilized by the SFA to describe the input-output relation of an organization.

One of the characteristics of the SFA is the application of this method allows researchers to conduct statistical analysis of the significance of the results obtained (Jarzebowski, 2013). Besides that, SFA is also found to offer a richer specification if given a panel data; compared to its non-parametric counterpart, DEA (Hjalmarsson, Kumbhakar and Heshmati, 1996). According to the same researchers, SFA also allows a formal statistical testing of hypothesis as well as the construction of confidence intervals. However, this also means that the production frontier would be generating all of the data in this research which is not consistent with embodied technical progress and a putty-clay technology. Last but not least, researchers Silva, Tabak, Cajueiro & Dias (2017) had also agreed to the advantages of SFA in a way that SFA is able to provide a general relationship relating outputs and inputs of organization and at the same time also accounts for random shocks.

The SFA model suggested by Battese and Coelli (1992) could be specified as follows:

$$Y_{it} = f(X_{it};\beta) + \varepsilon_{it}$$

Where:

Y_{it} = output of firm i (i=1,2,…n) at time t (t=2,…,T_i)

f() = Production technology

X = vector of n inputs

β = vector of unknown parameters

ε_{it} = error term (could also be expressed in $\varepsilon_{it} = v_{it} - u_{it}$)

3.2.4.2 Data Envelopment Analysis (DEA)

The non-parametric method that uses DEA to measure efficiency is first proposed by Charnes, Cooper & Rhodes, (1978) to assess the relative efficiency of a number of organizations by using the common set of inputs to generate a common set of outputs. DEA is mostly used to compare the productivity of similar organizations which are referred to as Decision Making Units (DMU). According to researchers Silva, Tabak, Cajueiro & Dias (2017), DEA assumes that there is a production frontier which is constructed using suitable combinations of inputs and outputs that the algorithm would estimate by using a piecewise linear hull which envelopes the empirical data observations. Other researchers had also added that

DEA is to be used as a deterministic tool where the analytical basis is an optimization problem instead of a production frontier (Jarzebowski, 2013).

Besides that, DEA also possesses the following characteristics such as it does not have any restrictive assumptions about technology to be made with an exception for convexity, it does not require any distributional assumptions about efficiency and all variations between production units is interpreted as inefficiency due to the lack of stochastic specification imposed. (Hjalmarsson, Kumbhakar & Heshmati, 1996). Last but not least, DEA does not require prior knowledge of the distributional form of inefficiency and the production technology to carry out its duty which gives it an edge over the SFA.

The basic DEA model suggested by Charnes-Cooper-Rhodes (CCR) could be specified as follows:

Maximize $$h_k = \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}}$$

Subject to

$$\frac{\sum_{r=1}^{s} u_r y_j}{\sum_{i=1}^{m} v_i X_j} \leq 1, j = 1,2, \ldots j_k, \ldots, n$$

$$u_r \geq \varepsilon, r = 1,2, \ldots, s$$

$$v_i \geq \varepsilon, i = 1,2, \ldots, m$$

Where:

v_i = Weights to be determined for input i

m= number of inputs

u_r = weights to be determined for output r

s = number of outputs

h_k = relative efficiency of DMU_k

n = number of entities

ε = small positive value

3.2.4.3 Verdict

Although DEA and SFA are both powerful tools that could be used to measure the efficiency of an organization, but in this research we would select SFA as our main tool to measure the efficiency of a 10 airports in the Oceania continent. This is because despite DEA’s advantages over SFA such as not requiring distribution assumptions and does not have restrictive assumptions about technology it still has its own limitations that would create unnecessary problems and biases that would affect the outcome of or research.

For instance, DEA is an extreme point technique which could not tolerate any unexplained variations. Any noise in a DEA model such as measurement error or even symmetrical noise with zero mean could cause significant problems and in turn affect the outcome of the efficiency estimated. Besides that, DEA is only good at estimating relative efficiency but could not perform equally at estimating absolute efficiency of an organization. In simple terms, DEA could only tell how well an organization performs compared to its competitors but not comparing it to the theoretical maximum efficiency. Furthermore, it is difficult to perform statistical hypothesis test on DEA due to its limitations as a nonparametric technique. This hampers most researches that are focusing on testing statistical hypothesis like our research. Lastly, DEA that creates a separate linear program for each organization could also be challenging for problems with a large amount of inputs and outputs that would be computationally intensive. Therefore, all these limitations of the DEA had justified our selection of the SFA as our efficiency measurement tool in this research.

3.3 Input-Output Specification

In this subtopic, we would provide a brief introduction about the inputs and outputs that our research had selected to measure the efficiency of airports in the Oceania continent. The selection of all inputs and outputs in this study that would be used to generate the technical efficiency value using the SFA method is based on one of our anchor journals Tsui, Gilbey & Balli (2014). All inputs and outputs are identified from the journal and were adopted in our study without any modifications and alterations. Other researchers such as Curi, Gitto & Mancuso (2011), Ahn & Min (2014), and Chow, Fung & Law (2016) had also adopted similar inputs and outputs in their own research regarding airport efficiency in different regions of the world. Therefore this justifies our rational adoption of the selected inputs and outputs in our study pertaining the efficiency of airports in the Oceania continent.

3.3.1 Input Specifications

3.3.1.1 Operating Expenses

The first input that we have selected for our study is the operating expenses of the 10 airports that we have pinpointed in the Oceania continent namely Adelaide, Brisbane, Melbourne, Perth, Sydney, Auckland, Christchurch, Wellington, Queenstown and Dunedin. Operating expenses of an airport is defined as the amount of money that needs to be spent in order to keep an airport operational. For this study, we’ve extracted the data from the published annual reports of the airports spanning from year 2007 to year 2016, with the unit of measurement denominated in their respective local currency.

The rationale behind our choice is that operating expenses acts as an indicator of resources spent maintaining the operational status of the airport. For instance, operating expenses includes the procurement of machineries, payroll of employees and the maintenance of infrastructure all of which are crucial to the airport. Therefore, it yields huge significance in measuring the efficiency of an airport. Some researchers had also adopted this input in their study that is used to determine the technical and allocative efficiency of airports in other regions of the world. (Coto-Millán et al., 2016)

3.3.1.2 Number of Runways

The second input that we have selected for our study is the number of runways that is currently available at the 10 airports pinpointed for our research. The number of runways of an airport is defined as the number of runways that could be utilize by commercial airliners for take-off and landing. Therefore, taxiways and airstrips within the vicinity of the airport that could not handle commercial airliners are not included in the data. For this study, we’ve extracted the data from the published annual reports of the airports spanning from year 2007 to year 2016 and compiled it for analysis.

The rationale behind our choice is that runways are the lifeline of an airport; the number of runways available could be used as a theoretical maximum for the handling capacity of an airport. Then, the theoretical maximum number could be used to compare against the passengers and aircraft movements data we obtained which would inform us about the efficiency of these airports that we are going to study. Therefore, it yields huge significance in measuring the efficiency of an airport; some researchers had also adopted this input in their study that is being used to determine the technical and allocative efficiency of airports in other regions of the world. (Ahn & Min, 2014)

3.3.2 Output Specifications

3.3.2.1 Operating Revenue

The first output that we have selected for our study is the operating revenue of the 10 airports that we have pinpointed in the Oceania continent. Operating revenue of an airport is defined as the total amount of proceeds the airport collected by maintaining its operational status without accounting for expenses. For this study, we’ve extracted the relevant data from the published annual reports of the airports spanning from year 2007 to year 2016 with the unit of measurement denominated in their respective local currency.

The rationale behind our choice is that operating revenue acts as a performance indicator of an airport that best reflects the achievement of these airports monetarily. For instance, operating revenue of an airport comes from the passenger service charge, aircraft parking fees, commercial space rentals, etc., all of which directly reflects the efficiency of an airport. An airport’s ability to maximize the operating revenue with a fix input would definitely be considered as efficient. Therefore, the operating revenue yields huge significance being a part of an equation that determines the efficiency of an airport. Researchers such as Tsui, Gilbey & Balli (2014) had also adopted a similar output in their study that is used to determine the technical and allocative efficiency of airports in other regions of the world.

3.3.2.2 Air Passenger Movement

The second output that we have selected for our study is the air passenger movement of the 10 airports that we have pinpointed in the Oceania continent. Air passenger movement of an airport is defined as the total number of passengers arriving and departing via the airport. For this study, we’ve compiled the data of air passenger movement from published annual reports by airports as well as the local statistics department that spans from year 2007 to year 2016.

The rationale for choosing this output is similar to the previous output. The number of air passenger movement could best reflect the performance of an airport given inputs such as operating expenses as well as the number of runways. The more air passenger movements the airport could handle, the nearer it is to its theoretical maximum which would equate to a higher efficiency. Therefore, the air passenger movement is considered significant to the measurement of airport efficiency. Other researchers such as Chang, Yu & Chen (2013) had also adopted a similar output in their study that is used to determine the technical and allocative efficiency of airports in other regions of the world.

3.3.2.3 Aircraft Movement

The third output that we have selected for our study is the aircraft movement of the 10 airports that we have pinpointed in the Oceania continent. Aircraft movement of an airport is defined as the total number of aircraft that took-off and landed via the airport. For this study, we’ve compiled the statistics from published annual reports of airports, local statistics department as well as local civil aviation authorities. The data that we compiled spans from year 2007 to year 2016.

The rationale behind our choice is simple. The number of aircraft movements is one of the best quantifiable indicators of performance in the airport industry. The closer the number of aircraft movements handled by the airport to the theoretical maximum, the more efficient the airport is. Therefore, the aircraft movement is considered significant to the measurement of airport efficiency. Other researchers such as Chow, Fung & Law (2016) had also adopted a similar output in their study that is used to determine the technical and allocative efficiency of airports in other regions of the world.

3.4 Data Description

In this study, other than determining the efficiency of 10 pinpointed airports in the Oceania continent using SFA, it would also include the linear regression analysis to determine the effects of internal and macroeconomic factors on the efficiency. Therefore, in this part of the study we would give a brief introduction about the internal and macroeconomic factors that we would be using in this study. The selection of these variables as the independent regressors for the linear regression could be justified based on a few of models retrieved from our anchor journals Tsui, Gilbey & Balli (2014). The selected variables were mostly originated from the abovementioned journals which contains an exactly identical variable. Therefore, this justifies the rational use of these variables in our current study regarding airport efficiency in the Oceania continent.

3.4.1 Internal Variable

3.4.1.1 Workload Unit (WLU)

Airport size plays a crucial role in our research as one of the internal variable in affecting airport efficiency. It is the size of operation in airport which includes adjacent utility buildings like terminals and hangars. Economies of scale can be achieved by enhancing the scale of operations and development of airports can also be improved at the same time. It is expressed as Workload Unit (WLU). The airport size is shown to have a positive relationship with the airport efficiency, meaning that larger airport size will have higher achievement on the airport overall efficiency in term of technical and environmental efficiency.

3.4.1.2 Percentage of International Traffic (IT)

Percentage of international traffic is defined as how much international traffic require for services and resources including passport, customs and quarantine control and also facilities for handling passenger, airmail and luggage. It is critical to take this variable into account in determining airport efficiency. Sophisticated facilities and infrastructures will be needed when there is high percentage of airport traffic to serve the international travellers especially larger airport capacity. These facilities will cause high expenses to the airport operation and also the operation to be more complex. It is expressed in percentage. The higher the percentage of international traffic, the lower the airport efficiency, indicating every increase in percentage of international traffic will cause the airport operation tougher and hence bring down the airport productivity.

3.4.1.3 Airport Operating Hours (AOH)

The airport operating hours in our study is referred to as the total hours that an airport is operating a year. The operating hours are different across the countries as there might be curfew that mandated by government and closed to the public overnight for security reasons, while there is some country that allows the airport to operate 24 hours. This variable studies the airport efficiency and productivity across the countries and the effect on economic growth when there is increase demand of air travel and air traffic volume.

3.4.1.4 Airport Ownership Dummy (OWN)

The airport ownership dummy variable in our study is used to differentiate the ownership status of the 10 airports in the Oceania continent which had been pinpointed for this study. While compiling the data for analysis, we found that the airports that we've pinpointed have different ownership structures with some majorly owned by regional governments, while some are privately owned with the government as the minority shareholder. In order to find out how this ownership structure affects the efficiency of the respective airports, we've decided to include this variable in our linear regression analysis. Airports that are majorly owned by private corporations are given the dummy '1', while airports that are majorly owned by regional governments are given the dummy '0'. In our opinion, profit based private corporations would be more efficient compared to non-profit based government organization given lesser bureaucracy and better transparency.

3.4.2 Macroeconomic Variables

3.4.2.1 Airport Hub Dummy (HUB)

Airport hub is one of the macroeconomic variable that we used in this research which define as an airport used and concentrated by many airlines with flight operation allocations to many different destinations, where people can travel from one country or city to other countries or cities in the presence of hub-and-spoke system. We have divided it into 2 categories which are international hub and regional hub. International hub airport is more efficiency compare to regional hub airport because it has the ability to attract more customers which will influence the output. The data that used is in dummy form. We set the airport with international hub as '1= hub' and the regional hub as '0 = non-hub'. When the air passenger movements increases as well as aircraft movements will cause an increase in the efficiency of airport.

3.4.2.2 Gross Domestic Product (GDP) per capita (GDP)

GDP is defined as the value of gross domestic product that are produced in the total economic output of a country. GDP per capita is a measure of the country's total output by the number of people in the population. A larger GDP per capita signals a better economic environment in Oceania mean that consumers will spend more on vacation and travel. When increases the air passenger movements at the airport as well as aircrafts movements will need to serve the demand which influencing the output measure of the efficiency. The data that has been used is in Ln GDP per capita, we take the natural log of GDP per capita in each year from year 2007 to 2016. Logarithms are defined as an opportune method in term of expressing large numbers. The data that used is in current US dollar (Australian bureau of statistics, 2017) (Statistics New Zealand, 2017). This indication of GDP is used for the measurement on the growth of monetary value for each person upon the population. The vibrant nature of changes on beyond the economic growth can be viewed not just in overall but also relative to the country size. When increase in Ln GDP per capita will cause an increasing in the efficiency of airport.

3.4.2.3 City Population (CP)

City population is the total number of persons inhabiting a city. We have chosen to use city population as external variables is to find out how large of the population can affect the efficiency of the airport. The unit measurement for city population that we have been used in data is in per capita. City population will affect the airport's efficiency based on the economic condition. A positive growth in economic will help to increase the efficiency level of the airport as the consumer will demand more.

3.4.2.4 Percentage of International Passenger (IP)

International passenger can be defined as person from other country come across to our country for travelling. In order to obtain a more accurate data, we had included international passenger in our data others than only involve domestic passenger. The data that we have been used is in percentage. The efficiency of airport can be seen not just affected by domestic passenger but also international passenger. Airport efficiency seems to be more affected by external business environment compare to airport's own ability to utilize its resources.

3.4.3 Interaction Variables

3.4.3.1 City Population Multiply Workload Unit (CP*WLU)

This variable is meant to create an interaction between the macroeconomic variable of city population and the internal variable of workload unit to expand the understanding of relationships among the variables in the model which then allows more hypotheses to be tested. The main purpose of this variable is to find out the combined effects of city population and the airport's workload unit on the technical efficiency of the research targets.

3.4.3.2 GDP per capita multiply Workload Unit (GDP*WLU)

Similar to the previous interaction variable, GDP*WLU is an interaction variable that creates a relationship between both variables of ln GDP per capita and workload unit which originates from two different models. The creation of this variable is to help expand the understanding of relationships among the variables and find out the combined effects of ln GDP per capita and workload unit on the technical efficiency of our research targets.

3.4.3.3 Airport Hub Dummy multiply Workload Unit (HUB*WLU)

The HUB*WLU variable is an interaction variable that helps establishes a relationship between the variables of airport hub dummy and the workload unit. This variable helps us to understand the relationships among the variables better and find out the combined effects of the airport hub dummy and the workload unit on the technical efficiency of our research targets which are the airports of the Oceania continent.

3.4.3.4 Percentage of International Passenger multiply Workload Unit (IP*WLU)

Having the same function as the other interaction variables that we've introduced just now, IP*WLU is an interaction variable that forms a relationship between the percentage of international passengers and the workload unit to help us understand more about the relationships among the variables. The IP*WLU helps to find out the combined effects of the percentage of international passenger and the workload unit on the technical efficiency of our research targets.

3.5 Econometric Framework

3.5.1 Estimating the Technical Efficiency

$$TE_{it} = \frac{TP_{it} + TAM_{it} + TOR_{it}}{f(TOE_{it} + NOR_{it}; \beta) + \varepsilon_{it}}$$

Where:

TE = Technical Efficiency

TP = Total Passengers

TAM = Total Aircraft Movements

TOR = Total Operating Revenue

TOE = Total Operating Expenses

NOR = Number of Runways

i = Airport of Adelaide, Brisbane,……, Dunedin

t = Year 2007, 2008, ……., 2016

ε_{it} = Error Term

β = Vector of Unknown Parameters

As depicted in the model above, we have substituted the inputs and outputs determined for this study to calculate the technical efficiency of the 10 airports that we have pinpointed by adopting the model which is first proposed by Battese & Coelli (1992). The calculations are conducted using a computer by running a programme written by Coelli named Frontier Version 4.1 and the final outcome of the calculations is provided in the form of technical efficiency.

3.5.2 Linear Regression Analysis (Internal Variables/Model 1)

$$TE_{it} = \beta_0 + \beta_1 WLU_{it} + \beta_2 OWN_{it} + \beta_3 AOH_{it} + \beta_4 IT_{it} + \varepsilon_{it}$$

Where:

TE = Technical Efficiency

WLU = Workload Unit

OWN = Ownership Dummy

AOH = Airport Operating Hours

IT = Percentage of International Traffic

β_0 = y-intercept

i = Airports of Adelaide, Brisbane, ….., Dunedin

t = Year 2007, 2008, ….., 2016

ε_{it} = Error Term

Armed with the technical efficiency estimated by Frontier Version 4.1, we regressed it against four independent internal variables using a statistical software known as EViews to find out the correlation between these independent variables and the technical efficiency. In other words, we find out on what scale the internal independent variables sway the technical efficiency of our research targets in the Oceania continent. The internal variables are factors that could be fully controlled and manipulated by the airports itself. This model that regresses technical efficiency against four independent internal variables would hereinafter be known as Model 1.

3.5.3 Linear Regression Analysis (Macroeconomic Variables/Model 2)

$$TE_{it} = \beta_0 + \beta_1 CP_{it} + \beta_2 GDP_{it} + \beta_3 HUB_{it} + \beta_4 IP_{it} + \varepsilon_{it}$$

Where:

TE = Technical Efficiency

CP = City Population

GDP = ln GDP per Capita

HUB = Airport Hub Dummy

IP = Percentage of International Passenger

β_0 = y-intercept

i = Airports of Adelaide, Brisbane, ….., Dunedin

t = Year 2007, 2008, ….., 2016

ε_{it} = Error Term

Similar to the linear regression analysis in 3.5.2, the technical efficiency that we've obtained using the programme Frontier Version 4.1 is used to regress against four macroeconomic variables. By using a statistical software known as EViews, we are able to find out the correlation between these macroeconomic variables also known as external variables and the technical efficiency. Besides that, it also gauges how far these variables sway the technical efficiency of the pinpointed airports in our research. These macroeconomic variables are factors which are beyond the control of the airport authorities and could not be manipulated whatsoever within its own means. This model that regresses technical efficiency against four independent macroeconomic variables would hereinafter be known as Model 2.

3.5.4 Linear Regression Analysis (Interaction Variables/Model 3)

$$TE_{it} = \beta_0 + \beta_1 CP * WLU_{it} + \beta_2 GDP * WLU_{it} + \beta_3 HUB * WLU_{it} + \beta_4 IP * WLU_{it} + \varepsilon_{it}$$

Where:

TE = Technical Efficiency

CP*WLU = City Population Multiply Workload Unit

GDP*WLU= ln GDP per Capita Multiply Workload Unit

HUB*WLU = Airport Hub Dummy Multiply Workload Unit

IP*WLU= Percentage of International Passenger Multiply Workload Unit

β_0 = y-intercept

i = Airports of Adelaide, Brisbane, ….., Dunedin

t = Year 2007, 2008, ….., 2016

ε_{it} = Error Term

By using the same linear regression analysis utilized in the two previous models, the interaction variables are regressed against the technical efficiency values obtained using the programme Frontier Version 4.1. EViews is then used to find out the correlation between the technical efficiency values and these interaction variables. By looking into the p-value of the variables, we could also gain an insight on which are the few variables that is significant in affecting the technical efficiency of the airports that we have targeted for this research. The interaction variable is formed by interacting an internal variable with the macroeconomic variables of the targeted airports to obtain a more comprehensive perspective on the relationship between the independent variables and technical efficiency scores of the targeted airports. This model that regresses technical efficiency against four interaction variables would hereinafter be known as Model 3.

3.5.5 Pooled OLS, FEM, REM

According to Gujarati & Porter (2010), there are 3 ways to estimate the function of a panel data. The first way is the pooled ordinary least square (POLS) model, the second way being the fixed effects model (FEM), and the last would be the random effects model (REM). We would discuss these three models in detail below.

3.5.5.1 Pooled OLS (POLS)

In this POLS model, we would pool all observations to estimate a "main" regression which ignores the cross-section and time series nature of the data.

The following model would be used to estimate the POLS:

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} \dots + \beta_k X_{kit} + \mu_i + v_{it}$$

Where:

Y_{it} = Dependent variable observed for airport i in time t
$X_{(k)it}$ = Independent variables(s), k=1,2,3…
β_0 = Constant slope intercept
β_k = Coefficient for the independent variable(s), k=1,2,3…
μ_i = Unobserved cross-sectional effects
v_{it} = "Well behaved" error term / Idiosyncratic error term

In the model, *i* is the *i*th subject and *t* is the time period for the independent variables stated above. By pooling all of our observations together, we assume that the regressions coefficients are the same for all airports and there is no way to distinguish between airports; hence, creating a scenario where one airport is the same as another airport (Gujarati & Porter, 2010). Besides that, the same researcher had also stated that POLS assumes independent variables to be non-stochastic and strictly exogenous because it does not depend on current, past, and future values of the error term ε_{it}. Another assumptions made about POLS are assuming the error term to be $\varepsilon_{it} \sim iid\ (0, \boldsymbol{\sigma}^2_u)$, and that it is independently distributed with zero mean and constant variance. The final assumption made about POLS is it assumes that the error term is normally distributed.

By examining the POLS results, we would see that all regression coefficients are highly statistically significant, which is in line with prior expectations of a high R^2 value. However, the estimated Durbin-Watson statistic is low suggesting a possible autocorrelation or spatial correlation in the data. Other than that, the low Durbin-Watson statistic could also imply specification errors. The major problem with POLS is that it does not help to differentiate between the various airports that we have pinpointed for our study nor does it inform us the response of total cost to the independent variables over time is the same for all airports. In simple terms, by totalling the panel data we've collected on the airports, we camouflaged the heterogeneity that may exist among the data. As a result, it is possible that the error term is correlated with some of the explanatory variables included in the model which leads to the estimated coefficients being biased and inconsistent.

3.5.5.2 Fixed Effects Model (FEM) - Least Square Dummy Variable (LSDV)

Unlike the POLS model, the FEM-LSDV model allows heterogeneity to surface within the data by granting each entity its own intercept value. It is more reasonable for each entity to have its own intercept value due to them having their own special features such as managerial styles, marketing strategies and target customers. Despite each entity having its own intercept which may differ across subjects, the intercepts does not vary over time which implies it to be time invariant, thereby the name Fixed Effects Model.

By using the differential intercept dummy technique, we could allow the fixed effects intercept to vary among the entities, the model could be written as follows:

$$Y_{it} = \sum_{k=1} \beta_k X_{kit} + \sum_{n=1} \alpha_n D_n + v_{it}$$

Where

α_n = Coefficient for the individual-specific dummy variable, n=1,2,3…
D_n = Individual-specific dummy variable, where

1 = Observation related to individual n

0 = Otherwise

However, by using the LSDV model approach, we need to be beware of the dummy variable trap which could exist as a situation of perfect collinearity. We could avoid this by introducing only n-1 number of dummies.

3.5.5.3 Fixed Effects Model (FEM) – Within-Group Estimator (WG)

The FEM-WG model estimates a pool regression by eliminating the fixed effects, β_0, hence expressing the values of the dependent and independent variables for each entity as deviations from their respective mean value. The WG estimator is able to produce consistent estimates of the slope coefficients; however, they were inefficient due to having large variances compared to ordinary pooled regression result.

By using the WG estimators, time invariant variables would be eliminated due to differencing, because it does not change over time and could be subtracted away from the mean value of the variables.

The WG model could be written as follow:

$$y_{it} - \overline{y_\iota} = \sum_{k=1}^{a} \beta_k \left(X_{kit} - \overline{X_{k\iota}}\right) + v_{it} - \overline{v_\iota}$$

From the model above, we could see that the intercept and the unobserved individual effects due to time invariant are eliminated from the model, and this model explains the values of the dependent and independent variables for each entity as deviations from their respective mean value. Hence, WG estimation could be used to tackle the heterogeneity bias due to the elimination of the unobserved effects.

However, the WG estimator also had its own drawbacks such as it may distort the parameter values and remove any long run effects from the variables. Besides, the elimination of time invariant variables would also result in us not knowing how the dependent variable does reacts to these time invariant variable, but this would be the price to pay to avoid the correlation between error term and independent variable.

3.5.5.4 Random Effects Model (REM)

The REM is basically a regression with a random constant term. With us lacking knowledge about the true model, REM is a way for us to express this ignorance through the disturbance term. The idea of REM could be written as follow:

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \cdots + \beta_k X_{kit} + [\mu_i + v_{it}]$$

Where:

Y_{it} = Dependent variable observed for country *i* in time t

X_{kit} = Independent variable(s), k=1,2,3…

β_0 = Constant slope intercept

β_k = Coefficient for the independent variable(s), k=1,2,3…

μ_i = Unobserved cross-sectional effects

v_{it} = “Well behaved” error terms / Idiosyncratic error term

In REM, the omitted variable bias is removed by measuring the changes within a group and then grouping the number of omitted variable into an independent variable. It also assumes the individual effects to be uncorrelated with the explanatory variables which allow these individual effects to be interpreted as explanatory variables. Another point that we should pay attention to when conducting REM estimation is that the error component, $\mu_{i,}$ is not directly observable which is what known as unobservable or latent. However, this unobserved effects is considered to be randomized and acts as an interference from the population where the sample has been randomly selected.

3.5.5.5 Poolability F-Test (POLS vs. FEM)

This poolability F-Test is used to find out the fact that whether or not the regression model suffers from individual effects. It is also used to decide between POLS or FEM in a panel regression. We would first construct the null and alternative hypothesis as below:

Null Hypothesis: $H_0 : \mu_i = 0$ (POLS)

Alternative Hypothesis: $H_1: \mu_i \neq 0$ (FEM)

From the null hypothesis above, we know that the individual effects are equal to zero. In other words, the model does not suffer from individual effects and the POLS model should be applied due to the assumptions made that satisfy the OLS estimators. For the alternative hypothesis, individual effects are not equal to zero in the regression model. This means that the regression model in the alternative hypothesis contains individual effects and the FEM would be comparatively more efficient than POLS.

3.5.5.6 Breusch-Pagan Lagrange Multiplier (BP-LM) Test (POLS vs. REM)

This BP-LM test is used to determine the existence of random effects in the hypothesis that is depicted below. It is also used to decide between POLS and REM in a panel regression.

Null Hypothesis: $H_0 : \sigma_\mu^2 = 0$ (POLS)

Alternative Hypothesis: $H_1 : \sigma_\mu^2 \neq 0$ (REM)

In the null hypothesis, it assumes that the variances across the entities are zero. This implies homoscedasticity which fulfils the general assumptions of OLS which requires a constant variance across different entities. On the other hand, the alternative hypothesis is not equal to zero. This implies heteroskedasticity. In such events, the panel regression should be using REM instead of POLS to avoid any biases than could possibly occur.

3.5.5.7 Hausman Test (FEM vs. REM)

The Hausman test is used to evaluate the consistency of an estimator when compared to an alternative that is less efficient but is already known to be consistent (Greene, 2014). Besides, it is also used to decide between FEM and REM in a panel regression.

Null Hypothesis: H_0: cov (μ_{it} / X_{it}) = 0 (REM)

Alternative Hypothesis: H_1: cov (μ_{it} / X_{it}) ≠ 0 (FEM)

In the null hypothesis, there is no correlation between the explanatory variable and individual effect. This meets the assumptions made by the REM. However, if a correlation exists between the predictor variables and individual effects, both FEM and REM would be inefficient but with FEM remaining consistent due to the individual effects that is constant. In a nutshell, if both models are efficient, REM is preferred compared to FEM. Otherwise, FEM is preferred because it is still consistent while REM has been rendered inefficient and inconsistent.

3.5.6 Panel Unit Root Test

Panel unit root testing was generated from time series unit root testing which is used to investigate whether a variable in the panel of series is stationary (not a unit root) or non-stationary (a unit root). According to Kunst, Nell and Zimmermann

(2011), there are 5 types of panel unit root tests which are Levin-Lin-Chu test (LLC), Im, Pesaran and Shin Test (IPS), Breitung's test, Fisher- type test (ADF and PP tests) and Hadri test. However, in this study, we would only be focusing on two of the five tests mentioned which are the LLC and IPS test.

Based on univariate time series, panel unit root test is of higher power than time series unit root test by including heterogeneous cross section data into series. The main difference from time series testing of unit roots is panel unit roots need to consider the asymptotic behaviour between the cross-sectional dimension (N) and the time-series dimension (T). The way in which N and T converge to infinity is critical if one wants to determine the asymptotic behaviour of estimators and tests used for non-stationary panels (Kunst, Nell and Zimmermann, 2011).

Spurious regression could also be identified through the application of panel unit root tests such as LLC and IPS.

The general regression model used by most (though not all) panel unit root testing is:

$$\Delta y_{it} = a_i \, y_{i,t-1} + \sum_{j=1}^{pi} \gamma_j \, \Delta \, y_{i,t-j} + \varepsilon_{it} \text{ , where } a_i = \rho_i - 1$$

The null hypothesis for testing non stationarity (a unit root):

$H_{o:}$ $a_i = 0$

The alternative hypothesis is not common for the panel unit root test that based on the ADF regression:

$H_{1:}$ $a_i = a < 0$ for all panels.

$H_{1:}$ $a_i < 0$ for some panels.

3.5.6.1 Levin-Lin-Chu (LLC) Test

Levin and Lin is one of the first unit root test developed for panel data. LLC tests assume that there is a general panel unit root process, therefore the autoregressive coefficients are the same across the cross sections. Individual unit root tests have limited power. The power of a test is the probability of rejecting the null when it is false and the null hypothesis is unit root. It follows that we find too many unit roots.

LLC test is based on ADF regression model:

$$\Delta y_{it} = a_i + \beta_{0i} + \beta_{1i} t + \mathcal{E}_{it}$$

Where i = 1,2,3,…,N and t = 1,2,3,…,T

LLC suggest the following hypotheses:

H_0: each time series contains a unit root
H_1: each time series is stationary

Where the lag order p is permitted to vary across individuals.

Based on the series, the individual effect (β_{0i}) and time trend ($\beta_{1i}t$) are incorporated. Lagged dependent variable and restricted to be homogeneous in every units are crucial source of heterogeneity in the deterministic components. In addition, according to Levin, Lin and Chu (2002), the error process ($\mathcal{E}_{it}$) is assumed distribute independently across individual and follow stationary invertible ARMA process for each of the individual at:

$$\mathcal{E}_{it} = \sum_{i=1}^{\infty} \Theta_{ij}\, \mathcal{E}_{it-j} + \mathcal{E}$$

The necessary condition for the Levin-Lin-Chu test is √NT/T → 0, while sufficient conditions would be NT/T → 0 and NT/T → κ. (NT means that the cross-sectional dimension N is a monotonic function of time dimension T.) According to the authors, the statistic performs well when N lies between 10 and 250 and when T lies between 5 and 250. If T is very small, the test is undersized and has low power.

One disadvantage of the test statistic is that it relies critically on the assumption of cross-sectional independence. Moreover, the null hypothesis that all cross sections have a unit root is very restrictive. That is, it does not allow the intermediate case, where some individuals are subject to a unit root and some are not. If T is very large, then Levin et al. (2002) suggest individual unit root time-series tests. If N is very large (or T very small) usual panel data procedures are appropriate.

However, for panels of moderate size standard multivariate procedures may not be computationally feasible or sufficiently powerful and the LLC test seems to be more appropriate. Unfortunately, the LLC test has some limitations. First of all, the test depends crucially upon the independence assumption across individuals, and hence not applicable if cross sectional correlation is present.

But the major limitation is that the autoregressive parameters are considered being identical across the panel:

$$H_{0:}\ p_1 = p_2 = \dots = p_N = p\ = 0$$
$$H_{1:}\ p_1 = p_2 = \dots = p_N = p\ < 0$$

The null makes sense under some circumstances, but as Maddala and Wu (1999) pointed out, the alternative is too strong to be held in any interesting empirical cases. This limitation has been overcame by IPS (Im, Pesaran and Shin, 1997, 2003) which proposed a panel unit root test without the assumption of identical first order correlation under the alternative.

3.5.6.2 Im-Pesaran-Shin (IPS) Test

For this study we have also chosen the Im, Pesaran and Shin (IPS), which is based on the well-known Dickey-Fuller procedure. Im, Pesaran and Shin denoted IPS proposed a test for the presence of unit roots in panels that combines information from the time series dimension with that from the cross section dimension, such that fewer time observations are required for the test to have power.

Since the IPS test has been found to have superior test power by researchers in economics to analyze long-run relationships in panel data, we will also employ this procedure in this study. IPS begins by specifying a separate ADF regression for each cross-section with individual effects and no time trend:

$$\Delta y_{it} = a_i + p_i \, y_{it-1} + \sum_{j=1}^{p_i} \beta_{ij} \, \Delta \, y_{it-j} + \mathcal{E}_{it}$$

Where i = 1, 2, 3…, N and t = 1, 2, 3…, T

The null and alternative hypotheses are defined as:

$H_{0:}$ $\beta_{ij} = 0$
$H_{1:}$ $\beta_{ij} < 0$

Thus under the null hypothesis, all series in the panel are non-stationary processes; under the alternative, a fraction of the series in the panel are assumed to be stationary. This is in contrast to the LLC test, which presumes that all series are stationary under the alternative hypothesis. The errors $\mathcal{E}_{it}$ are assumed to be serially auto correlated, with different serial correlation properties and differing variances across units. IPS proposes the use of a group–mean Lagrange multiplier statistic to test the null hypothesis.

IPS use separate unit root tests for the *N* cross-section units. Their test is based on the Augmented Dickey-fuller (ADF) statistics averaged across groups. The ADF regressions (perhaps of differing lag lengths) are computed for each unit, and a standardized statistic computed as the average of the LM tests for each equation. After estimating the separate ADF regressions, the average of the t-statistics for p_i from the individual ADF regressions, t_{iT} (p_i) :

$$t_{NT} = \frac{1}{N} \sum_{i=1}^{n} t_{iT}(p_i \, \beta_i)$$

IPS also propose the use of a group–mean t - bar statistic, where the t statistics from each ADF test are averaged across the panel; again, adjustment factors are needed to translate the distribution of t -bar into a standard Normal variate under the null hypothesis. The t-bar is then standardized and it is shown that the standardized t-bar statistic converges to the standard normal distribution as N and $T \to \infty$. IPS (1997) showed that t-bar test has better performance when N and T are small. They proposed a cross-sectionals demeaned version of both test to be used in the case where the errors in different regressions contain a common time-specific component IPS demonstrate that their test has better finite sample performance than that of LLC. Kunst, Nell, and Zimmermann (2011) states that Monte Carlo simulations found that IPS test performed better than LLC test in small sample.

3.5.7 Robust Regression and Robustness Check

Knowing that there is a possibility our least square regression analysis has violated some common assumptions for regression; transformations could be carried out by logging our variables to enlarge its trend or to eliminate them for good from the model. However, these transformations are very unlikely to shed the influence of the outliers in the variables and some variables could be too crucial to be eliminated at all. Therefore, we would be using the robust regression analysis that is resistance to the influence of outliers among the variables. According to Susanti, Pratiwi, Sulistijowati H. & Liana (2014), in robust regression analysis, outliers were detected and eliminated to provide an unbiased prediction and estimation. It is one of the most important tools that researchers had to counter datasets that are plague with outliers and ensure that the resulting models are stout against outliers.

The most common estimation technique for robustness regression analysis would be known as the M estimation. The letter M in this estimation technique stands for maximum likelihood type. The following equation shows that the M-estimator is unbiased and has minimum variance.

$$\hat{\beta} = \beta_n(x_1 , x_2 , \dots , x_n)$$

Therefore, the M-estimator has the smallest variance estimator compared to other estimators of variance and cap β is other linear and unbiased estimator for β:

$$var(\hat{\beta}) \geq \frac{[\bar{\beta}]^2}{nE(\frac{d}{d\beta}\ln f(x_i\ ;\ \beta))^2}$$

M estimation is considered as an extension of the maximum likelihood which is a robust regression. Through this method we are able to eliminate some of the outlier data and minimize the residual function of ρ:

$$\hat{\beta}_M = \underset{\beta}{min}\,\rho(y_i - \sum_{j=0}^{k} x_{ij}\beta_j)$$

CHAPTER 4: RESULT AND INTERPRETATION

4.0 Introduction

In this chapter, we will discuss more about the result and interpretation for each empirical model. The purpose is to determine the relationship between dependent variable, efficiency level of airport and eight independent variable which separate into four internal variables and four external variables. Internal variables include workload unit, percentage of international traffic, operating hours and road distance, while external variables include city population, percentage of international passenger, airport hub dummy and GDP per capita. We had used Pooled Ordinary Least Square (POLS), Random Effect Model (REM) and Fixed Effect Model (FEM) to select the most efficient and best model. Other than that, the result of the interaction term will be cover in this chapter too. The result and method we used will be discuss in more detail in the following section with some table for further interpretation. Lastly, we will have a brief conclusion of the test result in the last section of this chapter.

4.1 Technical Efficiency (TE)

Technical efficiency acts as a dependent variable in this study to help us gauge the influence of various independent variables that could possibly affect the performance of the airports in the Oceania continent. However, in order to quantify the technical efficiency level of the various airports from 2007 to 2016 on the Oceania continent, a statistical software known as the Frontier Version 4.1 developed by researcher TJ Coelli is applied. The technical efficiency values derived using the statistical software would then act as the dependent variable for this study in all the models.

The derivation of the technical efficiency value starts with the construction of inputs and outputs that were determined to be suitable to measure the performance of the airports. In this study, we applied inputs such as operating expenses and the number of runways of the airports to measure how much resource is invested and owned by these airports. On the other hand for the outputs, we applied operating revenue, air passenger movement and aircraft movement to measure the performance and handling capacity of the airports.

Referring to Table 4.1, the DMU labelled in the table stands for decision making unit and each individual airport is an independent DMU. Besides that, the technical efficiency values that ranges from 0.0000 to 0.9999 also brings significant meaning. The technical efficiency values that are close to 0 are being less efficient, while those close to 1 are being more efficient. The value 0 in technical efficiency symbolizes complete inefficiency and 1 symbolizes complete efficiency, neither firms could attain extreme values such as 0 and 1. Therefore, the typical value of technical efficiency ranges from 0.0001 to 0.9999. According to Hung Chiang & W.L. Cheng (2014), firms that are technically inefficient are identified through a technical efficiency value of below 0.9, while those that are technically efficient has a value above 0.9. Based on Table 4.1 there are 65 out of 100 DMUs that is considered technically efficient under Hung Chiang & W.L. Cheng's rule.

In the year 2007 and 2008, of all the 10 airports that we have targeted for this research only three is considered to be technically efficient during the period with a technical efficiency value of more than 0.9. The airports are situated in Brisbane, Melbourne, and Sydney. Moving on to the year 2009, overall improvements on the technical efficiency of airports could be seen as the Christchurch airport had increased its technical efficiency value to over 0.9, becoming the fourth airport to be technically efficient. The other three technically efficient airports are similar to those in 2007 and 2008. Starting from the year 2010 to 2016, out of the ten airports that we have targeted for this research, eight of them are technically efficient with a TE value larger than 0.9. The airports included are the previous 4 airports that had achieved technical efficient status, and the other four airports are the Adelaide airport, Perth airport, Auckland airport, and the Wellington airport. However, there are two airports that had never been technically efficient from

2007 to 2016 with a maximum TE value of only 0.63 throughout the years. The airports are the Queenstown and Dunedin airports respectively.

Brisbane, Melbourne and Sydney airports are few of the ten airports that had achieved technical efficient status since the beginning of our data. However, this does not mean that the TE values have been stable for all of the time, it had been slightly fluctuating within the barriers of 0.9 throughout 2007 to 2016 with Brisbane and Sydney having a TE value higher than where it had started in 2007. On the other hand, Melbourne had experienced a dip in its TE value compared to where it had started off in year 2007.

For Christchurch airport, it had only gained its technical efficient status starting from year 2009. Since then, the airport's TE value had been climbing slowly and steadily. Starting off at 2009's 0.9460, the airport's TE value had rose to 0.9587 in 2016, a total difference of 0.0127, which could be considered as an impressive improvement.

The four airports of Adelaide, Perth, Auckland, and Wellington had only achieved its technical efficient status starting from year 2010 onwards. Since then, the TE value for Perth and Auckland airports have risen steadily throughout the period from 2010 to 2016. On the other hand, the TE value for Adelaide and Wellington airport had fluctuated slightly throughout the year 2010 to 2016, but both airports had ended up with a TE value higher than where it had started off. An improvement of 0.0038 in TE value could be observed for the Adelaide airport and an improvement of 0.0023 in TE value could be observed for the Wellington airport respectively.

There are two airports in our research that had not gained technical efficient status throughout the period of our research data, which are the Queenstown and Dunedin airport. All TE values for both the airports had shown ranked lower than 0.9 which does not matches the rule that is suggested by Hung Chiang & W.L. Cheng (2014). However, despite not achieving the technical efficient status, the TE values for both of the airports had also fluctuated throughout 2007 to 2016.

By thoroughly examining Table 4.1, we could see that Melbourne airport in year 2007 and 2008 is the most efficient within all of the airports that we studied by having a technical efficiency value of 0.9699; while the least efficient airport would be Dunedin in 2007 by having a technical efficiency value of 0.1915. After analysing the mean efficiency values of the airports we could see that the overall efficiency of airports throughout the years fluctuated consistently without any regular pattern observable. From the mean value, we could conclude that the best efficiency performance of all the 10 airports is attained in 2011with a mean score of 0.9011; while the worse efficiency performance of all the 10 airports is attained in 2007 with a mean score of 0.6176.

Besides that, if we examine Table 4.1 rigorously, we could also spot that all the technical efficiency values lies within the interval unit of zero (0) to one (1). The justification for this occurrence is provided by McDonald (2009), where the researcher had clearly stated in the journal that the minimum and maximum limit of technical efficiency values to be zero and one respectively. Hence, this had verified our efficiency scores to be valid all of which falls between the interval of zero and one.

DMU	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Adelaide	0.5951	0.6346	0.7695	0.9542	0.9525	0.9512	0.9563	0.9598	0.9615	0.9580
Brisbane	0.9360	0.9145	0.9194	0.9283	0.9381	0.9386	0.9583	0.9681	0.9685	0.9587
Melbourne	0.9699	0.9699	0.9697	0.9686	0.9679	0.9684	0.9600	0.9098	0.9195	0.9191
Perth	0.8834	0.8736	0.8003	0.9667	0.9700	0.9278	0.9674	0.9670	0.9671	0.9575
Sydney	0.9480	0.9624	0.9119	0.9560	0.9600	0.9603	0.9195	0.9198	0.9193	0.9290
Auckland	0.6127	0.6378	0.6580	0.9672	0.9663	0.9670	0.9693	0.9605	0.9188	0.9188
Christchurch	0.4738	0.5016	0.9460	0.9467	0.9437	0.9444	0.9472	0.9525	0.9549	0.9587
Wellington	0.3103	0.3341	0.8338	0.9509	0.9496	0.9498	0.9526	0.9551	0.9569	0.9532
Queenstown	0.2256	0.2451	0.2940	0.5918	0.6334	0.5927	0.5086	0.4738	0.5019	0.5889
Dunedin	0.1915	0.2072	0.3314	0.6364	0.6246	0.5470	0.4163	0.2839	0.6298	0.1940
Mean	0.6176	0.6341	0.7464	0.8983	0.9011	0.8897	0.8703	0.8551	0.8367	0.8191

Table 4.1
Value of Technical Efficiency from 2007 to 2016 for each airports based in Oceania continent.

4.2 Panel Unit Root Test

The unit root test can be used to identify stationarity of the data for the variables under investigation. Tests were performed the result of both LLC and IPS tests by using individual intercept and also using individual intercept and trend at level and 1^{st} Difference. If the p-value is less than 0.1, 0.05, or 0.01 which accord with anyone mean the null hypothesis is rejected, representing that the data is stationary and stable.

In LLC test, the results is shown in Table 4.2.1. At 1^{st} Difference, LLC certificate that all variables are stable at the 5% significance level under individual intercept and under individual intercept and trend. However, at level form only few variables are stationary. For the individual intercept, AOH is the only variable which can determine stationary at 1%. In individual intercept and trend all were stationary at the 1% significance level for the AOH, IT, GDP, IP, and IP*WLU variables.

The results of IPS test is shown in Table 4.2.2 IPS certificate that all variables are stable at 10% significance level with an individual intercept and with an individual intercept and trend at 1^{st} Difference. On the contrary, at level form AOH is stationary at 1% significance level in individual intercept and AOH and GDP both of the variables are stationary at 5% significance level in Individual Intercept and Trend.

In a nutshell, we can conclude that the test results are very satisfactory due to all the variables in 1^{st} difference in each methods reach stationary. All the tests commonly named as “Panel Unit Root” tests. Through these tests, we can avoid the spurious result problem and confirm the variables are constant.

Variables	Levin, Lin, Chu			
	Individual Intercept		Individual Intercept and Trend	
	Level	1st Difference	Level	1st Difference
TE	-127.619***	-103.980***	-105.617***	-76.6495***
AOH	-5.80271***	-7.51839***	-7.40904***	-6.13326***
IT	-0.89515	-6.63555***	-2.98570***	-7.65966***
WLU	3.81964	-4.38859***	1.28789	-7.82626***
CP	2.37668	-1.66029**	2.93185	-16.2273***
CP*WLU	4.78225	-3.59332***	0.34243	-4.50737***
GDP	-0.81293	-11.3877***	-9.31238***	-12.6040***
GDP*WLU	2.42859	-6.01568***	-0.07301	-9.30663***
IP	-1.21819	-7.63158***	-4.25414***	-6.79709***
IP*WLU	1.53811	-7.48621***	-2.97945***	-7.69297***
HUB*WLU	3.83105	-2.63643***	2.40300	-7.16536***

TABLE 4.2.1

Notes: *, **and *** implies that the rejection of the null hypothesis of non-stationary at 10%, 5% and 1% significance level respectively.

Variables	Im, Pesaran, Shin			
	Individual Intercept		Individual Intercept and Trend	
	Level	1st Difference	Level	1st Difference
TE	-31.2875***	-54.2018***	-48.8225***	-21.1208***
AOH	-3.86723***	-6.58863***	-1.80063**	-2.31721**
IT	2.39829	-4.15464***	-0.45180	-1.32548*
WLU	4.95804	-2.85014***	0.79068	-1.59318*
CP	7.83781	-4.56606***	3.04025	-1.90384**
CP*WLU	5.63675	-3.18562***	0.23382	-3.78236***
GDP	1.95106	-5.63099***	-1.89351**	-2.19396**
GDP*WLU	3.91065	-3.84863***	0.14327	-1.44363*
IP	0.81516	-3.36707***	-0.18205	-1.32435*
IP*WLU	3.64519	-3.39235***	0.38414	-1.34250*
HUB*WLU	4.92075	-2.06155**	0.65999	-1.52191*

TABLE 4.2.2

Notes: *, **and *** implies that the rejection of the null hypothesis of non-stationary at 10%, 5% and 1% significance level respectively.

4.3 Model Comparison

Here we have models for three variables, which are macro variable, internal variable and interaction variable. To select the best model to determine the airport technical efficiency, we have regressed several models including POLS, FEM and REM to test our data for the variables with different assumption from different models.

4.3.1 POLS

From the POLS model, the regression results show that the model for Model 2 is statistically significant with R squared of 0.643066. Variables of gross domestic product (GDP) and airport hub dummy (HUB) are found to be statistically significant while city population (CP) and internal passengers (IP) are having the different sign from our theoretical expectation and are insignificance. Besides for city population (CP) which is significant at 5%, gross domestic product (GDP) and airport hub dummy (HUB) are statistically significant at 1% significant level. The variable of internal passengers (IP) is not significant in the model.

For Model 1, the model is having goodness of fit of 0.581304, indicating 58.13 percent of the variation in dependent variable is explained by the linear relationship between independent variable and dependent variable. Most of the variables are significance including airport ownership dummy (AOT), ownership dummy (OWN) and workload unit (WLU), except for percentage of international traffic (IT) which is insignificant. Other than international traffic (IT) which is insignificant, other variables, airport ownership dummy (AOT), ownership dummy (OWN) and workload unit (WLU), are significance to the dependent variable at significance level of 1%.

Furthermore, Model 3 has higher R squared of 0.674488, indicating a higher goodness of fit. In this model, only GDP*WLU is found to be significant. Other variables are statistically insignificant, including CP*WLU, HUB*WLU and

IP*WLU. Variables GDP*WLU and HUB*WLU are found to be statistically significant at 1% significant level.

4.3.2 REM

By comparing POLS and REM, they have consistent result in sign, sharing same sign of significance in every variables. The overall goodness of fit of the three model are higher compared to POLS model. It get higher from 0.643066 to 0.671482 in macro variable and increase from 0.653126 from 0.581304 in internal variable. In interaction variables, goodness of fit raise to 0.737391 from 0.674488. It representing that REM model fits the data better.

In Model 2, variables of city population (CP) and internal passengers (IP) are showing negative result from our expectation while gross domestic product (GDP) and airport hub dummy (HUB) are still significant, same as the result in POLS model. Gross domestic product (GDP) and airport hub dummy (HUB) are statistically significant at 1% significance level. The city population (CP) is statistically significant at 5% significance level.

For Model 1, most of the variables are significant in the model. Airport ownership dummy (AOT), ownership dummy (OWN) and workload unit (WLU) are found to be statistically significant at 1% significant level. However, international traffic is not significant toward the dependent variable.

Besides, Model 3 shows that most of the variables are not significant including CP*WLU, HUB*WLU and IP*WLU. Only variable of GDP*WL is found to be significant at 1% significant level.

4.3.3 FEM

By comparing POLS and FEM, the findings are similar. By using FEM, it showed the highest goodness of fit among the model of POLS, REM and FEM. In the model of FEM, data of the variables can explain the relationship between dependent variable and independent variable the best.

Comparing FEM to POLS, the independent variables are showing the same sign of significance level no matter in which model. The results are similar, the significant variables in POLS model are still significant in FEM model.

In model of macro variables, gross domestic product (GDP), airport hub dummy (HUB) are significant at 1% of significant level while city population is significant at significant level of 5%. In the model for internal variables, airport ownership dummy (AOT), ownership dummy (OWN) and workload unit (WLU) are statistically significant at 1%. While in model of interaction variables, variables GDP*WLU and HUB*WLU are found to be statistically significant at 1% significant level. Other than that, all other variables are found not significant towards the dependant variable.

Model 1			
Model	POLS	FEM	REM
C	-0.198515 (0.155482)	-0.238205 (0.129946)*	-0.227418 (0.131995)*
AOH	0.000105 (2.21E-05)***	0.000112 (1.85E-05)***	0.000110 (1.85E-05)***
IT	-0.002232 (0.003309)	-0.003876 (0.002783)	-0.003429 (0.002777)
OWN	0.178192 (0.049872)***	0.195463 (0.041766)***	0.190762 (0.041720)***
WLU	5.91E-09 (1.97E-09)***	5.61E-09 (1.65E-09)***	5.69E-09 (1.65E-09)***
R-squared	0.581304	0.736342	0.653126
Adjusted R-squared	0.563674	0.696486	0.638521
D-W test stat	0.692672	0.823176	0.774688

Table 4.3.1

Note: The asterisks *, **, *** indicate rejection of the null hypothesis at 10%, 5% and 1% level of significance respectively. Standard Error in parentheses.

Model 2			
Model	POLS	FEM	REM
C	-8.905849 (1.074005)***	-8.479663 (1.006274)***	-8.647078 (0.988255)***
CP	-2.52E-08 (1.14E-08) **	-2.27E-08 (1.04E-08)**	-2.37E-08 (1.03E-08)**
GDP	0.882692 (0.099832)***	0.843101 (0.093458)***	0.858646 (0.091797)***
HUB	0.336623 (0.058873)***	0.325359 (0.052862)***	0.329686 (0.052761)***
IP	-0.002088 (0.001711)	-0.001803 (0.001531)	-0.00191 (0.001530)
R-squared	0.643066	0.742034	0.671482
Adjusted R-squared	0.628038	0.703039	0.65765
D-W test stat	0.81144	0.834805	0.82374

Table 4.3.2

Note: The asterisks *, **, *** indicate rejection of the null hypothesis at 10%, 5% and 1% level of significance respectively. Standard Error in parentheses.

Model 3			
Model	POLS	FEM	REM
C	-3.343796 (0.437121)***	-3.076074 (0.365169)***	-3.138374 (0.364925)***
CP*WLU	-0.071875 (0.049529)	-0.031906 (0.041800)	-0.041228 (0.041592)
GDP*WLU	0.383871 (0.126275)***	0.287391 (0.106222)***	0.309857 (0.105773)***
HUB*WLU	-4.95E-09 (1.77E-09)***	-5.52E-09 (1.47E-09)***	-5.39E-09 (1.47E-09)***
IP*WLU	-0.034449 (0.039959)	-0.018295 (0.033202)	-0.022035 (0.033156)
R-squared	0.674488	0.799034	0.737391
Adjusted R-squared	0.660782	0.768655	0.726334
D-W test stat	0.871375	1.070564	1.005505

Table 4.3.3

Note: The asterisks *, **, *** indicate rejection of the null hypothesis at 10%, 5% and 1% level of significance respectively. Standard Error in parentheses.

4.4 Comparison Test

We had carried out several additional test in order to choose the best fit model to explain the airport technical efficiency based on our macro variable, internal variable, and interaction variable.

4.4.1 Model 1

As for the internal variable, we had also conducted the same additional test as 4.4.1 in order to select the best model to fit and explain our data. Firstly, Likelihood Ratio (LR) test had been carried out in order to compare POLS and FEM. The result for this test shows a test statistic of 5.618911 with a p-value of 0.0000 which is smaller than the significance level of 1%/5%/10%. Since the p-value is smaller than significance level, the null hypothesis is rejected and we have enough evidence to prove that FEM is preferable than POLS.

Next, we performed Lagrange Multiplier (LM) test to compare between POLS and REM. The result for this test shows test statistic of 39.07122 which is higher than the critical value of 7.289, 4.321 and 2.952 at the significance level of 1%, 5%, and 10% respectively. Since that the test statistic is higher than the critical value, the null hypothesis is rejected and we have enough evidence to prove that the REM is better than POLS.

Lastly, after carrying out both LM and LR test knowing that FEM and REM is better than POLS, another test which is Hausman test was carried out in order to choose the best model. The test had showed the test statistic of 16.007548 with the p-value of 0.0011. Since the p-value is smaller than the significance level of 1%/5%/10%, therefore, we can conclude that the REM is inconsistent and inefficient, and the FEM is the best model to fit our data.

	LR Test	LM Test	Hausman Test
Test Statistic	5.618911***	39.07122***	16.007548***
Decision Making	Reject null hypothesis	Reject null hypothesis	reject null hypothesis
Conclusion	FEM is preferable compared to POLS	REM is preferable compared to POLS	FEM is preferable compared to REM

Table 4.4.1

Notes: *, ** and *** implies that the rejection of the null hypothesis at 10%, 5% and 1% significance level respectively.

4.4.2 Model 2

Firstly, we had performed Likelihood Ratio (LR) test for comparison of POLS and FEM. The result for this test statistic is 3.665951 with the p-value of 0.0000 which is smaller than the significance level of 1%/5%/10%. Since the p-value is smaller than significance level, the null hypothesis is had been rejected, we had enough evidence to prove that FEM is better than POLS.

Next, we then performed Lagrange Multiplier (LM) test for the comparison between POLS and REM. The result had shown that the test statistic of 17.15043 which is higher than the critical value of 7.289, 4.321, 2.952 at the significance level of 1%, 5%, 10% respectively. Therefore, we have enough evidence to conclude that REM is better than POLS as null hypothesis had rejected.

Lastly, after carrying out both LM and LR test knowing that FEM and REM is better than POLS, another test which is Hausman test was carried out in order to choose the best model. The result of this test shown that the test statistic of 6.254784, but the p-value of this test is 0.1809 which is higher than the significance level of 1%/5%/10%. Therefore, we do not reject null hypothesis, we can conclude that FEM is inefficient and REM is the best model to fit our panel data.

	LR Test	LM Test	Hausman Test
Test Statistic	3.665951***	17.15043***	6.254784
Decision Making	Reject null hypothesis	Reject null hypothesis	Do not reject null hypothesis
Conclusion	FEM is preferable compared to POLS	REM is preferable compared to POLS	REM is preferable compared to FEM

Table 4.4.2
Notes: *, ** and *** implies that the rejection of the null hypothesis at 10%, 5% and 1% significance level respectively.

4.4.3 Model 3

For the interaction variable, we had conducted several additional test same as 4.4.1 and 4.4.2. Firstly, we had performed Likelihood Ratio (LR) test to compare between POLS and FEM. The result of this test showed a test statistic of 5.921926 where its p-value is 0.0000 which is lower than the significance level of 1%/5%/10%. Since the p-value is smaller than the significance level, the null hypothesis is rejected, and we have enough evidence to prove that FEM is preferable than POLS.

Next, we carried out the Lagrange Multiplier (LM) test to compare between POLS and REM. The result of this test has a test statistic of 42.05511 where the value is higher than the critical value of 7.289, 4.321, and 2.952 at the significance level of 1%, 5%, and 10% respectively. Therefore, REM is more preferable compared to POLS as the null hypothesis of LM test had been rejected.

Lastly, after carrying out both LM and LR test knowing that FEM and REM is better than POLS, another test which is Hausman test was carried out in order to choose the best model. The result has a test statistic of 7.146137 with a p-value of 0.1284 which is higher than the significance level of 1%/5%/10%. Therefore, we do not reject null hypothesis, and we can conclude that FEM is inefficient while REM is the best model to fit our panel data.

	LR Test	LM Test	Hausman Test
Test Statistic	5.921926***	42.05511***	7.146137
Decision Making	Reject null hypothesis	Reject null hypothesis	Do not reject null hypothesis
Conclusion	FEM is preferable compared to POLS	REM is preferable compared to POLS	REM is preferable compared to FEM

Table 4.4.3
Notes: *, ** and *** implies that the rejection of the null hypothesis at 10%, 5% and 1% significance level respectively.

4.5 Random Effect Model (REM) and Fixed Effect Model (FEM)

In order to choose whether REM or FEM should be used, we had applied hausman specification test which also known as Durbin-Wu-Hausman test for each empirical model.

As we can view from the result, all the model showed the same result of Likelihood Ratio Test and Lagrange Multiplier (LM) Test, only a little bit different in Hausman Test. Likelihood Ratio Test for all the model showed that FEM are outperform simply pooled OLS as the probability value is 0.0000 which is less than 0.05 significance level. The Lagrange Multiplier (LM) Test also showed a probability value of 0.0000 which is less than 0.05 significance level, thus REM is more prefer than pooled OLS for all the three model.

Whereas, The Hausman Test for the model consist of macroeconomics variables showed a higher probability, 0.1809 than significant level, 0.05. Thus, the model for macroeconomics variables is more prefer to REM.

The model for interaction variables will be more prefer to REM too as the probability is 0.1284 also higher than the 0.05 significance level. There is insufficient evidence to conclude that FEM is more suitable than REM. Thus, REM is preferred for interaction variables.

Lastly, model with internal variables will be prefer to FEM rather than REM. As the probability showed that 0.0011 in Hausman test is lower than the 0.05 significance level. Thus, the null hypothesis is rejected and there is sufficient evidence that using FEM is more suitable than REM.

4.6 Robust Regression and Robustness Check

4.6.1 Model 1

Referring to Table 4.6.1, by comparing least square regression analysis FEM and robust regression analysis FEM for Model 1, we are able to identify some minute changes in terms of the error term and p-value. Besides that, after the elimination of outlying observations in the variables through robust regression analysis, the number of significant variables in the model remained unchanged. However the p-value for these significant variables had increase or decrease slightly to adjust for the elimination of outliers in the dataset of the variables.

The variables AOH, OWN and WLU all had experienced a rise in their standard error which resulted in the increase in their p-value. Despite that, their significance remains unchanged which is still deemed to be significant at 5% significance level.

Model 1		
Model	Least Square Regression FEM	Robust Regression FEM
C	-0.238205 (0.129946)*	-0.238205 (0.230161)
AOH	0.000112 (1.85E-05)***	0.000112 (3.57E-05)***
IT	-0.003876 (0.002783)	-0.003876 (0.003372)
OWN	0.195463 (0.041766)***	0.195463 (0.092571)**
WLU	5.61E-09 (1.65E-09)***	5.61E-09 (2.10E-09)***
R-squared	0.736342	0.736342
Adjusted R-squared	0.696486	0.696486
D-W test stat	0.823176	0.823176

Table 4.6.1

Note: The asterisks *, **, *** indicate rejection of the null hypothesis at 10%, 5% and 1% level of significance respectively. Standard Error in parentheses.

4.6.2 Model 2

Referring to Table 4.6.2, by comparing least square regression analysis REM and robust regression analysis REM for Model 2, we are able to identify some minute changes in terms of the error term and p-value. Besides that, after the elimination of outlying observations in the variables through robust regression analysis, the number of significant variables at 1% significance level in the model had increased. This is most likely due to the adjustment of p-value in these variables which had decrease slightly to account for the elimination of outliers in the dataset of the variables.

All variables in Model 2 has experienced a rise in standard error in the robust regression analysis, except for HUB which experienced a slight decrease. As a result, the p-value of CP and IP decreases and increases respectively due to the changes in the standard error. With all these changes, the p-value for CP, GDP, HUB is less than 0.01 which makes them significant at 1% significance level. Compared to the least square regression analysis which only had GDP and HUB to be significant at 1% significance level, therefore it could be considered as an improvement to the model.

Model 2		
Model	Least Square Regression REM	Robust Regression REM
C	-8.647078 (0.988255)***	-8.647078 (1.432193)***
CP	-2.37E-08 (1.03E-08)**	-2.37E-08 (7.86E-09)***
GDP	0.858646 (0.091797)***	0.858646 (0.132030)***
HUB	0.329686 (0.052761)***	0.329686 (0.048337)***
IP	-0.00191 (0.001530)	-0.00191 (0.001740)
R-squared	0.671482	0.671482
Adjusted R-squared	0.65765	0.65765
D-W test stat	0.82374	0.82374

Table 4.6.2

Note: The asterisks *, **, *** indicate rejection of the null hypothesis at 10%, 5% and 1% level of significance respectively. Standard Error in parentheses.

4.6.3 Model 3

Referring to Table 4.6.3, by comparing least square regression analysis REM and robust regression analysis REM for Model 3, we are able to identify some minute changes in terms of the error term and p-value. Besides that, after the elimination of outlying observations in the variables through robust regression analysis, the number of significant variables in the model remained unchanged. However, the p-value for all variables in the model had decreased slightly as an adjustment for the elimination of outliers in the dataset of the variables.

All variables in Model 3's robust regression REM had experienced a fall in their standard error which resulted in the decrease of p-value. Despite that, only GDP*WLU and HUB*WLU had achieved its significance at 1% significance level. The decrease in p-value for the other two variables is not sufficiently extreme to turn the variables into significant even at 10% significance level.

Model 3		
Model	Least Square Regression REM	Robust Regression REM
C	-3.138374 (0.364925)***	-3.138374 (0.170817)***
CP*WLU	-0.041228 (0.041592)	-0.041228 (0.028748)
GDP*WLU	0.309857 (0.105773)***	0.309857 (0.067427)***
HUB*WLU	-5.39E-09 (1.47E-09)***	-5.39E-09 (6.71E-10)***
IP*WLU	-0.022035 (0.033156)	-0.022035 (0.028879)
R-squared	0.737391	0.737391
Adjusted R-squared	0.726334	0.726334
D-W test stat	1.005505	1.005505

Table 4.6.3

Note: The asterisks *, **, *** indicate rejection of the null hypothesis at 10%, 5% and 1% level of significance respectively. Standard Error in parentheses.

4.7 Chapter Summary

The overview for the data analysis is to identify the preferred model for macroeconomics variables, interaction variables and internal variables by applying Breush and Pagan LM Test, Likelihood Ratio Test and Hausman Test. As we can see from the result, macroeconomics and interaction variables have the same prefer model which is REM as the probability is higher than significant level for both of the model. Besides, according to our research showed that most of the variables showed a significant result in POLS model which include gross domestic product (GDP), airport hub dummy (HUB), city population (CP), airport ownership dummy (AOT), ownership dummy (OWN), workload unit (WLU), GDP*WLU and HUB*WLU. Next, we only found international traffic, CP*WLU, HUB*WLU and IP*WLU is not significant in REM. Moreover, variables which significant in POLS are still significant in FEM. Last but not least, the significant result is explained by each airport's preferred model.

CHAPTER 5: CONCLUSION

5.0 Introduction

The principal objective of this research is to investigate and measure the efficiency of airports from the view of panel data analysis. By using a secondary data for our sample of study, we composed 3 series of data for a total of 10 different airports across 10 years, which is from year 2007 to 2016 in the Oceania continent countries (5 airports from Australia and 5 airports from New Zealand). In addition, our intention on this study is to test the relationship between each variable (internal, external and interaction) and technical efficiency. In this chapter, we will proceed into 4 parts which as a summary and essence of this whole research. Firstly, we will summarize the findings of our research and also based on our findings to suggest a few policy implications. Next, we will determine the limitations that throughout in our study so as to improve our future knowledge economy analysis. For future research reference, we also have provided and make some recommendations for future researcher in order to avoid those problems.

5.1 Summary of Finding

This research applies a two-stage analysis methodology to determine the technical efficiency level of the research target and identify the factors that could possibly sway the technical efficiency level. The first stage of our analysis involves the utilization of the Stochastic Frontier Analysis (SFA) method to determine the efficiency level of our research targets. The SFA method is used to quantify the technical efficiency level of the various airports by crunching the inputs and outputs numbers of the airport using computer software. According to our findings, 65 out of 100 of the Decision Making Units (DMU) we’ve included in our research had attained a status of being technical efficient by having a technical efficiency value of more than 0.9 which is determined by researchers Hung

Chiang & W.L. Cheng (2014). While the remaining 35 DMUs are deemed to be technically efficient with a technical efficiency value of lower than 0.9. These technical efficiency values is then recorded and carried forward to the second stage of our analysis.

In the second stage analysis of our research, we regressed the technical efficiency values with three different sets of independent variables and generated 9 different models which includes POLS, FEM, and REM for each set of independent variables. By using tests such as the Langrange Multiplier (LM), Likelihood Test, and Hausman Test; we are able to eliminate six models that are deemed not suitable. For the first set of independent variables which are internal variables, FEM is the preferred model. There are three variables that are statistically significant at 1% significant level which are Airport Operating Hours (AOH), Airport Ownership Dummy (OWN), and Workload Unit (WLU). For the second set of independent variables which are the macroeconomic variables, REM is the preferred model. There are two variables that are statistically significant at 1% significant level which are ln GDP per capita (GDP) and the Airport Hub Dummy (HUB); there is another variable that is statistically significant at 5% significant level which is city population (CP). For the third set of independent variables which are the interaction variables, REM is also the preferred model. There are two variables that are statistically significant at 1% significant level which are ln GDP per capita multiply Workload Unit (GDPXWLU) and Airport Hub Dummy multiply Workload Unit (HUBXWLU).

After undergoing such a long process for the study, we are finally able to answer the research questions that we have posed during the very first chapter of this study. First of all, the complete table of technical efficiency level of the targeted airports in the Oceania continent can be found in Table 4.1, and we have also found that only a portion of internal, macroeconomic and interaction variable are able to create an impact on the technical efficiency and performance of airports. By referring to Table 4.3.1 to Table 4.3.3, we could observe variables that are significant are marked with asterisk (*). This means that, variables that are marked with asterisk are capable and significant enough to influence the technical efficiency and performance of airports. However, some variables such as city population (CP) in Model 2, workload unit (WLU) and airport operating hours (AOH) in Model 1, and airport hub dummy multiply workload unit (HUB*WLU) are found to be significant but less impactful to the technical efficiency values of the airport. This is based on the low coefficient that is obtained during the econometrics test. In Table 4.3.1 to Table 4.3.3, Model 1 represents set of internal variables; Model 2 represents set of macroeconomic variables, while Model 3 represents set of interaction variables.

By able to answer the research questions, we have achieved all of our research objectives which is to investigate the relationships between variables as well as to study the technical efficiency level. Throughout our study, some clarifications were also made in relation to the questions that we have posed in the problem statement of the study. By referring to the technical efficiency Table 4.1, we could see that most airports have an improving track record throughout the years from 2007 to 2016. Most airports had attained a status of efficient starting from year 2010, except for two government owned airports that has yet to achieve that status. In year 2016, all but two airports that we have conducted our researched on is operating with a relatively high efficiency score compared to previous years. However, it has yet to reach its maximum efficiency and further improvements could be made to maximize the efficiency of the airports before any plans to build extra infrastructure that would the tax payer their hard earn money. Besides that, we have also proven the relationship between GDP per capita of countries in the Oceania continent and the efficiency of the airport industry. The variable of GDP is significant and its coefficient is positive which means that it is a positive relationship. Last but not least, through this study we had also found out that airports that are owned by governments are likely to perform inefficiently. For instance, Queenstown and Dunedin airports are both owned by their regional governments and has yet to achieve the status of an efficient airport.

5.2 Implication of Study

From our study, we found that all three models that we have analysed contains variables that are significant and is capable of influencing the technical efficiency of airports in the Oceania continent. However, not all variables are able to create a meaningful impact on the technical efficiency values despite their proven significance based on its observed coefficient. In order to increase the competitiveness of the airports within their country, governments are allowed and encouraged to step in with policies that would benefit the development and advancement of airports. But, prudent decisions should be considered by the government when implementing policy changes that are related to the airport industry.

For instance, in Model 1, airport operating hours, ownership status and the workload unit of an airport is significant in influencing the technical efficiency of airports. However, workload unit (WLU) and airport operating hours (AOH) are considered to be less impactful based on their very small coefficient value which implies little to no change to the technical efficiency of the airports. Prudent and reasonable actions should be taken by the government to improve the performance of airports based on the discovery and factor in all the considerations and concerns before making any changes to the current policy. Despite having little to no impact to the airport’s technical efficiency level, government bodies such as the Department of Civil Aviation could establish a rule that governs the non-stop operation of airports in the country. This allows airports to extend their operations hours and hence enhancing their capability in handling more flights and passengers which would translate into a higher workload unit of the airport. Lawmakers could also write a law governing airport operators to extend their operation hours to 24 hours a day before the concession of the airport shall be granted. This allows airports to have longer operating hours and experience a rise in workload units which is beneficial to the airport’s efficiency. Besides that, regional governments could also choose to divest their stakes in airports that are not efficient as our study found that the ownership status of an airport is significant in influencing its efficiency. The participation of private investors is likely to increase the efficiency of airports due to the status change in ownership.

Furthermore in Model 2, city population, GDP, and the hub status of an airport is found to be significant in influencing the technical efficiency of airports. However, city population (CP) is considered to be less impactful based on their very small coefficient value which implies little to no change to the technical efficiency value of the airports. Despite city population having little to no impact to the airport's technical efficiency level, central and regional governments could still try to give out tax rebates and tax breaks to individuals and companies that are willing to move to the cities that have been targeted. This is because the GDP variable has been proven to be not only significant but very impactful to the increase of airport efficiency in a region. The tax breaks then creates a domino effect which attracts companies and corporations to invest in the region which would increase the local GDP per capita in the region which would draw employments into the region that increases its population. Governments could launch affordable housing projects, and building community infrastructure such as hospitals, schools, parks, etc. to keep the population growing at a steady pace. With a sustainable city population growth in place, it would also contribute positively to the increase in airport efficiency. Last but not least, with the increase in city population, strong demands of air services in the region, governments could approve the airport's hub status which would also positively contribute to the rise in airport efficiency.

Finally, in Model 3, ln GDP per capita multiply Workload Unit and Hub Status multiply Workload Unit is found to be significant in influencing the technical efficiency of airports. However, Hub Status multiply Workload unit (HUBXWLU) is considered to be less impactful based on their very small coefficient value which implies little to no change to the technical efficiency value of the airports. Similar actions could be taken by the central and regional government by providing tax breaks and tax rebates to companies, corporations, and individuals to attract investments into the region. The rise in GDP that comes mainly from these investments increases the workload unit of the airport. When more and more people travel to the region to seek for employment and leisure, the flights and cargoes that the airport needs to handle increases thus the rise in the workload unit. The rise in workload unit caused by the rise in GDP would reflect positively on the airport's efficiency. Despite having little to no impact to the airport's efficiency, governments could still approve the hub status of airports which diverts more aerial traffic towards the airport. By handling more traffic, the workload unit of the airport would eventually rise thus indirectly increasing the efficiency of airports in the region.

The government also plays an important role when it comes to dealing with the technological gap in airport technology. Governments could launch initiatives such as introducing adjustable lane technology and variable speed limits to help airports overcome the landing difficulties by airplanes during bad weather. With this technology, less planes would need to be diverted and thus a rise in airport revenue and its efficiency. Besides that, government agencies such as the Department of Civil Aviation should also establish a law to ensure compulsory retraining for air traffic control staffs as well as airport crews at a fixed interval to ensure that they were updated with the latest skills and understand the changes in their working environment to minimize any errors that could lead to a drop in efficiency or even worse, a fatal accident.

5.3 Limitations

Based on our study, there are a few limitations we had encountered to be proposed for further studies. First of all, we are lack of information for the data of internal and external output. There are limited amount of literature to support our research paper. In the beginning of our research, we only have four independent variables that has direct relationship with our dependant variable. To overcome this problem, we collected the correlation between our dependant variable, and it gives us a wider array of eight independent variables which can classify as internal and external factors.

Other than that, there are a few of the variable are not significant. We had collected the empirical data of 100 observations, and yet the R-Square from our test is quite low. This problem shows that the independent variables from our data are not able to fully explain our dependant variable. This may affect our model to be imperfect as the variable are inadequate. We hope that future researcher may look for more appropriate variables so that they can measure the dependent variable better.

5.4 Recommendations

In this part, we will propose some recommendation to future researchers for future studies to be improved. Firstly, we highly recommended the future study researcher may include the latest updated data in their paper. This is because latest updated data set can increase the accuracy and explanatory power of the model and lead the model to be more efficiency in estimation.

Next, as we only focus on 10 airports from year 2007 to year 2016 to examine the impact of those variables on technical efficiency in this study. So, the sample size in our research is considered as a small sample size data. In order to get an accurate statistical analysis, sample size need to be increase to larger sample size. In model, smaller sample size may be the root of heteroscedasticity. Therefore, future researchers can comprise more countries' airport and take longer time period to enlarge the sample size in the research.

As refer in the limitation of research, low R-squared values were a problematic when we need precise predictions. As the solution, future researchers can enhance the efficiency of the research by increasing the number of variables in the model. The objective of adding more variables also can reduce the omitted variables bias that will break down the assumptions of BLUE estimator to avoid spurious results problem.

Lastly, we suggest that further researchers can through others methodology like ADF, PP, panel co-integration and so on to capture the accuracy and efficiency of the variables. As example, in ADF has a non-parametric test which does not require for select the level of serial correlation which called PP test. It rather takes the same estimation scheme as in DF test, but will correct the statistic to conduct for autocorrelations and heteroscedasticity (HAC type corrections).

REFERENCES

Abdullah, H., & Kumaran, V. (2015). Long-Run Relationship Between Technical Efficiency of GLCs and Macroeconomic Factors: Evidence Using Pedroni's Cointegration Approach. Advanced Science Letters, 21(6), 2063-2067. http://dx.doi.org/10.1166/asl.2015.6207

Adler, N., Liebert, V., & Yazhemsky, E. (2013). Benchmarking airports from a managerial perspective. *Omega*, *41*(2), 442-458. http://dx.doi.org/10.1016/j.omega.2012.02.004

Aigner, D., Lovell, C., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal Of Econometrics*, *6*(1), 21-37. http://dx.doi.org/10.1016/0304-4076(77)90052-5

A mixed bag of opportunities and challenges for airports - ADB SAFEGATE. (2018). *ADB SAFEGATE*. Retrieved 9 April 2018, from https://adbsafegate.com/airport-performance/challenges/

Ahn, Y., & Min, H. (2014). Evaluating the multi-period operating efficiency of international airports using data envelopment analysis and the Malmquist productivity index. *Journal Of Air Transport Management*, *39*, 12-22. http://dx.doi.org/10.1016/j.jairtraman.2014.03.005

Australia Bureau of Statistics. (2017). *5206.0 - Australian National Accounts: National Income, Expenditure and Product, Dec 2017*. *Abs.gov.au*. Retrieved 9 April 2018, from http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/5206.0Dec%202017?OpenDocument

Balistreri, E., McDaniel, C., & Wong, E. (2003). An estimation of US industry-level capital–labor substitution elasticities: support for Cobb–Douglas. *The North American Journal Of Economics And Finance*, *14*(3), 343-356. http://dx.doi.org/10.1016/s1062-9408(03)00024-x

Barros, C. (2008). Airports in Argentina: Technical efficiency in the context of an economic crisis. *Journal Of Air Transport Management*, *14*(6), 315-319. http://dx.doi.org/10.1016/j.jairtraman.2008.08.005

Battese, G., & Coelli, T. (1992). Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India. *Journal Of Productivity Analysis*, *3*(1-2), 153-169. http://dx.doi.org/10.1007/bf00158774

Bottasso, A., Conti, M., & Piga, C. (2012). Low-cost carriers and airports' performance: empirical evidence from a panel of UK airports. *Industrial And Corporate Change*, *22*(3), 745-769. http://dx.doi.org/10.1093/icc/dts033

Chang, Y., Yu, M., & Chen, P. (2013). Evaluating the performance of Chinese airports. *Journal Of Air Transport Management*, *31*, 19-21. http://dx.doi.org/10.1016/j.jairtraman.2012.11.002

Charnes, A., Cooper, W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal Of Operational Research*, *2*(6), 429-444. http://dx.doi.org/10.1016/0377-2217(78)90138-8

Chi-Lok, A., & Zhang, A. (2009). Effects of competition and policy changes on Chinese airport productivity: An empirical investigation. *Journal Of Air Transport Management*, *15*(4), 166-174. http://dx.doi.org/10.1016/j.jairtraman.2008.09.003

Chow, C., Fung, M., & Law, J. (2016). Regional Development and Airport Productivity in China. *Advances In Airline Economics*, 283-316. http://dx.doi.org/10.1108/s2212-160920160000005011

Christensen, L., Jorgenson, D., & Lau, L. (1973). Transcendental Logarithmic Production Frontiers. *The Review Of Economics And Statistics*, *55*(1), 28. http://dx.doi.org/10.2307/1927992

Coelli, T. (2005). *An introduction to efficiency and productivity analysis*. New York, NY: Springer.

Coto-Millán, P., Casares-Hontañón, P., Inglada, V., Agüeros, M., Pesquera, M., & Badiola, A. (2014). Small is beautiful? The impact of economic crisis, low cost carriers, and size on efficiency in Spanish airports (2009–2011). *Journal Of Air Transport Management*, *40*, 34-41. http://dx.doi.org/10.1016/j.jairtraman.2014.05.006

Coto-Millán, P., Inglada, V., Fernández, X., Inglada-Pérez, L., & Pesquera, M. (2016). The "effect procargo" on technical and scale efficiency at airports: The case of Spanish airports (2009–2011). *Utilities Policy*, *39*, 29-35. http://dx.doi.org/10.1016/j.jup.2016.01.004

Crockatt, M. (2000). *Airport Infrastructure And Regional Development A Case For Resurrecting The Growth Pole Concept* (Master). University of Manitoba.

Curi, C., Gitto, S., & Mancuso, P. (2011). New evidence on the efficiency of Italian airports: A bootstrapped DEA analysis. *Socio-Economic Planning Sciences*, *45*(2), 84-93. http://dx.doi.org/10.1016/j.seps.2010.11.002

Doganis, R. (1992). *The airport business*. London: Routledge.

Farrell, M. (1957). The Measurement of Productive Efficiency. *Journal Of The Royal Statistical Society. Series A (General)*, *120*(3), 253. http://dx.doi.org/10.2307/2343100

Ferreira, D., Marques, R., & Pedro, M. (2016). Comparing efficiency of holding business model and individual management model of airports. *Journal Of Air Transport Management*, *57*, 168-183. http://dx.doi.org/10.1016/j.jairtraman.2016.07.020

Fung, M., Wan, K., Hui, Y., & Law, J. (2008). Productivity changes in Chinese airports 1995–2004. *Transportation Research Part E: Logistics And Transportation Review*, *44*(3), 521-542. http://dx.doi.org/10.1016/j.tre.2007.01.003

Gujarati, D., & Porter, D. (2010). *Basic econometrics*. [USA]: McGraw-Hill/Irwin.

Ha, H., Wan, Y., Yoshida, Y., & Zhang, A. (2013). Airline market structure and airport efficiency: Evidence from major Northeast Asian airports. *Journal Of Air Transport Management*, *33*, 32-42. http://dx.doi.org/10.1016/j.jairtraman.2013.06.008

Hjalmarsson, L., Kumbhakar, S., & Heshmati, A. (1996). DEA, DFA and SFA: A comparison. *Journal Of Productivity Analysis*, *7*(2-3), 303-327. http://dx.doi.org/10.1007/bf00157046

Hung Chiang, Y., & W.L. Cheng, E. (2014). Estimating contractors' efficiency with panel data. *Construction Innovation*, *14*(3), 274-291. http://dx.doi.org/10.1108/ci-07-2013-0033

Im, K., Pesaran, M., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal Of Econometrics*, *115*(1), 53-74. http://dx.doi.org/10.1016/s0304-4076(03)00092-7

Jarzębowski, S. (2013). *Parametric And Non-Parametric Efficiency Measurement - The Comparison Of Results*, *XIV*(1), 170-179. Retrieved from http://yadda.icm.edu.pl/yadda/element/bwmeta1.element.desklight-e5956898-bdc4-4775-b622-f52b20b67645/c/MIBE_T14_z1_16.pdf

Kan Tsui, W., Balli, H., Gilbey, A., & Gow, H. (2014). Operational efficiency of Asia–Pacific airports. *Journal Of Air Transport Management*, *40*, 16-24. http://dx.doi.org/10.1016/j.jairtraman.2014.05.003

KMENTA, J. (1967). AN ECONOMETRIC MODEL OF AUSTRALIA, 1948–61. *Australian Economic Papers*, *5*(8), 131-164. http://dx.doi.org/10.1111/j.1467-8454.1967.tb00777.x

Kokkinou, A. (2009). Stochastic Frontier Analysis: Empirical Evidence on Greek Productivity. In *The 4th HO PhD Symposium on Contemporary Greece and Cyprus*. London School of Economics. Retrieved from http://www.lse.ac.uk/europeanInstitute/research/hellenicObservatory/pdf/4th_%20Symposium/PAPERS_PPS/APPLIED_ECONOMICS/KOKKINOU.pdf

Kumaran, V., Abdullah, H., & Hussin, F. (2015). Measuring the Performance and Efficiency of top Listed Government Linked Companies (Glcs). Australian Journal Of Basic And Applied Sciences, 9(8), 101-104. Retrieved from http://ajbasweb.com/old/ajbas/2015/IPN%20Kuching%20Special/101-104.pdf

Kumbhakar, & Lovell, C. (2000). *Stochastic Frontier Analysis*. Cambridge, UK: Cambirdge University Press.

Kunst, R., Nell, C., & Zimmerman, S. (2011). Summary based on Chapter 12 of Baltagi: Panel Unit Root Tests. Retrieved from http://homepage.univie.ac.at/robert.kunst/pan2011_pres_nell.pdf

Maddala, G., & Wu, S. (1999). A Comparative Study of Unit Root Tests with Panel Data and a New Simple Test. *Oxford Bulletin Of Economics And Statistics*, *61*(s1), 631-652. http://dx.doi.org/10.1111/1468-0084.0610s1631

Marques, R., Simões, P., & Carvalho, P. (2014). The influence of the operational environment on efficiency of international airports. *Journal Of Advanced Transportation*, *49*(4), 511-522. http://dx.doi.org/10.1002/atr.1272

Martini, G., Manello, A., & Scotti, D. (2013). The influence of fleet mix, ownership and LCCs on airports' technical/environmental efficiency. *Transportation Research Part E: Logistics And Transportation Review*, *50*, 37-52. http://dx.doi.org/10.1016/j.tre.2012.10.005

McDonald, J. (2009). Using least squares and tobit in second stage DEA efficiency analyses. *European Journal Of Operational Research*, *197*(2), 792-798. http://dx.doi.org/10.1016/j.ejor.2008.07.039

Merkert, R., & Mangia, L. (2012). Management of airports in extreme winter conditions—some lessons from analysing the efficiency of Norwegian airports. *Research In Transportation Business & Management*, *4*, 53-60. http://dx.doi.org/10.1016/j.rtbm.2012.06.004

Merkert, R., & Mangia, L. (2014). Efficiency of Italian and Norwegian airports: A matter of management or of the level of competition in remote regions?. *Transportation Research Part A: Policy And Practice*, *62*, 30-38. http://dx.doi.org/10.1016/j.tra.2014.02.007

Ministry of Business, Innovation and Employment. (2016). International tourism forecasts interactive web tool. Wellington: Ministry of Business, Innovation and Employment.

Örkcü, H., Balıkçı, C., Dogan, M., & Genç, A. (2016). An evaluation of the operational efficiency of turkish airports using data envelopment analysis and the Malmquist productivity index: 2009–2014 case. *Transport Policy*, *48*, 92-104. http://dx.doi.org/10.1016/j.tranpol.2016.02.008

Ouattara, W. (2012). Economic Efficiency Analysis in Côte d'Ivoire. American Journal Of Economics, 2(1), 37-46. http://dx.doi.org/10.5923/j.economics.20120201.05

Oum, T., & Yu, C. (2004). Measuring airports' operating efficiency: a summary of the 2003 ATRS global airport benchmarking report. *Transportation Research Part E: Logistics And Transportation Review*, *40*(6), 515-532. http://dx.doi.org/10.1016/j.tre.2004.08.002

Oum, T., Adler, N., & Yu, C. (2006). Privatization, corporatization, ownership forms and their effects on the performance of the world's major airports. *Journal Of Air Transport Management*, *12*(3), 109-121. http://dx.doi.org/10.1016/j.jairtraman.2005.11.003

Oum, T., Yan, J., & Yu, C. (2008). Ownership forms matter for airport efficiency: A stochastic frontier investigation of worldwide airports. *Journal Of Urban Economics*, *64*(2), 422-435. http://dx.doi.org/10.1016/j.jue.2008.03.001

Oxford Dictionaries | English. (2017). *Oxford Dictionaries | English*. Retrieved 9 April 2018, from https://en.oxforddictionaries.com/definition/efficiency

Pathomsiri, S. (2006). *Assessment of Productive Efficiency of Airports* (Ph.D). University of Maryland.

Pavelescu, F. (2011). Some aspects of the translog production function estimation. *Romanian Journal Of Economics*, *32*(32/2011), 131-150. Retrieved from http://www.revecon.ro/articles/2011-1/2011-1-8.pdf

Perelman, S., & Serebrisky, T. (2012). Measuring the technical efficiency of airports in Latin America. *Utilities Policy*, *22*, 1-7. http://dx.doi.org/10.1016/j.jup.2012.02.001

Randrianarisoa, L., Bolduc, D., Choo, Y., Oum, T., & Yan, J. (2015). Effects of corruption on efficiency of the European airports. *Transportation Research Part A: Policy And Practice*, *79*, 65-83. http://dx.doi.org/10.1016/j.tra.2015.03.025

Rodríguez-Álvarez, A., Tovar, B., & Trujillo, L. (2007). Firm and time varying technical and allocative efficiency: An application to port cargo handling firms. *International Journal Of Production Economics*, *109*(1-2), 149-161. http://dx.doi.org/10.1016/j.ijpe.2006.12.048

Scotti, D., Malighetti, P., Martini, G., & Volta, N. (2012). The impact of airport competition on technical efficiency: A stochastic frontier analysis applied to Italian airport. *Journal Of Air Transport Management*, *22*, 9-15. http://dx.doi.org/10.1016/j.jairtraman.2012.01.003

See, K., & Li, F. (2015). Total factor productivity analysis of the UK airport industry: A Hicks-Moorsteen index method. *Journal Of Air Transport Management*, *43*, 1-10. http://dx.doi.org/10.1016/j.jairtraman.2014.12.001

Silva, T., Tabak, B., Cajueiro, D., & Dias, M. (2017). A comparison of DEA and SFA using micro- and macro-level perspectives: Efficiency of Chinese local banks. *Physica A: Statistical Mechanics And Its Applications*, *469*, 216-223. http://dx.doi.org/10.1016/j.physa.2016.11.041

Statistics New Zealand. (2017). *New Zealand in the OECD*. *Archive.stats.govt.nz*. Retrieved 9 April 2018, from http://archive.stats.govt.nz/browse_for_stats/government_finance/central_government/nz-in-the-oecd/gdp-per-capita.aspx

Susanti, Y., Pratiwi, H., Sulistijowati H., S., & Liana, T. (2014). M ESTIMATION, S ESTIMATION, AND MM ESTIMATION IN ROBUST REGRESSION. *International Journal Of Pure And Apllied Mathematics*, *91*(3). http://dx.doi.org/10.12732/ijpam.v91i3.7

Tan, B. (2008). *Cobb-Douglas Production Function*. Lecture, Universidade Nova de Lisboa.

The Guardian. (2017). Major airport delays in Australia and New Zealand as global passport system goes down. Retrieved from https://www.theguardian.com/world/2017/may/22/major-airport-delays-in-australia-and-new-zealand-as-global-passport-system-goes-down

The Treasury, New Zealand. (2017). MEI Special Topic: Outlook for the Dairy Sector. Wellington: The Treasury, New Zealand.

Tourism Research Australia. (2016). Tourism Forecast 2016. Canberra: Australia Trade and Investment Commission.

Tovar, B., & Martín-Cejas, R. (2010). Technical efficiency and productivity changes in Spanish airports: A parametric distance functions approach. *Transportation Research Part E: Logistics And Transportation Review*, *46*(2), 249-260. http://dx.doi.org/10.1016/j.tre.2009.08.007

Tsekeris, T. (2011). Greek airports: Efficiency measurement and analysis of determinants. *Journal Of Air Transport Management*, *17*(2), 140-142. http://dx.doi.org/10.1016/j.jairtraman.2010.06.002

Ülkü, T. (2014). *Emprirical analyses of airport efficiency and costs: Small regional airports and airport groups in Europe* (Master of Science). Humboldt University of Berlin.

Ülkü, T. (2015). A comparative efficiency analysis of Spanish and Turkish airports. *Journal Of Air Transport Management*, *46*, 56-68. http://dx.doi.org/10.1016/j.jairtraman.2015.03.014

Up with Airport Efficiency. (2017). *Saab Corporate*. Retrieved 28 June 2017, from http://saabgroup.com/Media/stories/stories-listing/2014-09/up-with-airport-efficiency/

Wanke, P. (2012). Capacity shortfall and efficiency determinants in Brazilian airports: Evidence from bootstrapped DEA estimates. *Socio-Economic Planning Sciences*, *46*(3), 216-229. http://dx.doi.org/10.1016/j.seps.2012.01.003

World Bank. (2017). Air transport, passengers carried | Data. Data.worldbank.org. Retrieved 2 July 2017, from http://data.worldbank.org/indicator/IS.AIR.PSGR?end=2015&locations=AU-NZ&start=2000

Zhao, Q., Choo, Y., & Oum, T. (2014). The Effect of Governance Forms on North American Airport Efficiency: A Comparative Analysis of Airport Authority vs. Government Branch. *Journal Of The Transportation Research Forum*, *53*(2 (Summer 2014), 93-110. Retrieved from http://ageconsearch.umn.edu/record/207437/files/2014v53n2_06_AirportEfficiency.pdf

Zou, B., Kafle, N., Chang, Y., & Park, K. (2015). US airport financial reform and its implications for airport efficiency: An exploratory investigation. *Journal Of Air Transport Management*, *47*, 66-78. http://dx.doi.org/10.1016/j.jairtraman.2015.05.002

APPENDICES

Model 1

(i) POLS

Dependent Variable: TE
Method: Panel Least Squares
Date: 02/07/18 Time: 16:28
Sample: 2007 2016
Periods included: 10
Cross-sections included: 10
Total panel (balanced) observations: 100

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.198515	0.155482	-1.276767	0.2048
AOH	0.000105	2.21E-05	4.762236	0.0000
IT	-0.002232	0.003309	-0.674700	0.5015
OWN	0.178192	0.049872	3.572996	0.0006
WLU	5.91E-09	1.97E-09	3.000912	0.0034

R-squared	0.581304	Mean dependent var	0.812515
Adjusted R-squared	0.563674	S.D. dependent var	0.257400
S.E. of regression	0.170025	Akaike info criterion	-0.657033
Sum squared resid	2.746315	Schwarz criterion	-0.526775
Log likelihood	37.85166	Hannan-Quinn criter.	-0.604315
F-statistic	32.97369	Durbin-Watson stat	0.692672
Prob(F-statistic)	0.000000		

(ii) FEM

Dependent Variable: TE
Method: Panel Least Squares
Date: 02/07/18 Time: 16:30
Sample: 2007 2016
Periods included: 10
Cross-sections included: 10
Total panel (balanced) observations: 100

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.238205	0.129946	-1.833103	0.0702
AOH	0.000112	1.85E-05	6.057306	0.0000
IT	-0.003876	0.002783	-1.392670	0.1673
OWN	0.195463	0.041766	4.679962	0.0000
WLU	5.61E-09	1.65E-09	3.406690	0.0010

Effects Specification

Period fixed (dummy variables)

R-squared	0.736342	Mean dependent var	0.812515
Adjusted R-squared	0.696486	S.D. dependent var	0.257400
S.E. of regression	0.141807	Akaike info criterion	-0.939525
Sum squared resid	1.729389	Schwarz criterion	-0.574801
Log likelihood	60.97624	Hannan-Quinn criter.	-0.791914
F-statistic	18.47536	Durbin-Watson stat	0.823176
Prob(F-statistic)	0.000000		

(iii) REM

Dependent Variable: TE
Method: Panel EGLS (Period random effects)
Date: 02/07/18 Time: 16:33
Sample: 2007 2016
Periods included: 10
Cross-sections included: 10
Total panel (balanced) observations: 100
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.227418	0.131995	-1.722927	0.0882
AOH	0.000110	1.85E-05	5.963054	0.0000
IT	-0.003429	0.002777	-1.234768	0.2200
OWN	0.190762	0.041720	4.572485	0.0000
WLU	5.69E-09	1.65E-09	3.458661	0.0008

Effects Specification

	S.D.	Rho
Period random	0.074536	0.2165
Idiosyncratic random	0.141807	0.7835

Weighted Statistics

R-squared	0.653126	Mean dependent var	0.418870
Adjusted R-squared	0.638521	S.D. dependent var	0.241478
S.E. of regression	0.145184	Sum squared resid	2.002446
F-statistic	44.71875	Durbin-Watson stat	0.774688
Prob(F-statistic)	0.000000		

Unweighted Statistics

R-squared	0.580137	Mean dependent var	0.812515
Sum squared resid	2.753968	Durbin-Watson stat	0.691586

(iv) LM Test (REM vs. POLS)

Lagrange multiplier (LM) test for panel data
Date: 02/07/18 Time: 16:02
Sample: 2007 2016
Total panel observations: 100
Probability in ()

Null (no rand. effect) Alternative	Cross-section One-sided	Period One-sided	Both
Breusch-Pagan	2.510942	39.07122	41.58217
	(0.1131)	(0.0000)	(0.0000)
Honda	1.584595	6.250698	5.540389
	(0.0565)	(0.0000)	(0.0000)
King-Wu	1.584595	6.250698	5.540389
	(0.0565)	(0.0000)	(0.0000)
SLM	3.544169	6.463402	--
	(0.0002)	(0.0000)	--
GHM	--	--	41.58217
	--	--	(0.0000)

(v) Likelihood Ratio (FEM vs. POLS)

Redundant Fixed Effects Tests
Equation: Untitled
Test period fixed effects

Effects Test	Statistic	d.f.	Prob.
Period F	5.618911	(9,86)	0.0000
Period Chi-square	46.249148	9	0.0000

Period fixed effects test equation:
Dependent Variable: TE
Method: Panel Least Squares
Date: 02/07/18 Time: 16:31
Sample: 2007 2016
Periods included: 10
Cross-sections included: 10
Total panel (balanced) observations: 100

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.198515	0.155482	-1.276767	0.2048
AOH	0.000105	2.21E-05	4.762236	0.0000
IT	-0.002232	0.003309	-0.674700	0.5015
OWN	0.178192	0.049872	3.572996	0.0006
WLU	5.91E-09	1.97E-09	3.000912	0.0034

R-squared	0.581304	Mean dependent var	0.812515
Adjusted R-squared	0.563674	S.D. dependent var	0.257400
S.E. of regression	0.170025	Akaike info criterion	-0.657033
Sum squared resid	2.746315	Schwarz criterion	-0.526775
Log likelihood	37.85166	Hannan-Quinn criter.	-0.604315
F-statistic	32.97369	Durbin-Watson stat	0.692672
Prob(F-statistic)	0.000000		

(vi) Hausman Test (FEM vs. REM)

Correlated Random Effects - Hausman Test
Equation: Untitled
Test period random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	16.007548	3	0.0011

Cross-section random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
AOH	-0.001984	0.000079	0.000002	0.1670
IT	0.041618	0.004946	0.000106	0.0004
WLU	-0.000000	0.000000	0.000000	0.4112

Cross-section random effects test equation:
Dependent Variable: TE
Method: Panel Least Squares
Date: 02/07/18 Time: 16:33
Sample: 2007 2016
Periods included: 10
Cross-sections included: 10
Total panel (balanced) observations: 100
WARNING: estimated coefficient covariance matrix is of reduced rank

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	15.96971	11.77404	1.356349	0.1785
AOH	-0.001984	0.001494	-1.328364	0.1875
IT	0.041618	0.011556	3.601440	0.0005
OWN	NA	NA	NA	NA
WLU	-2.85E-09	9.25E-09	-0.307667	0.7591

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.710152	Mean dependent var	0.812515
Adjusted R-squared	0.670173	S.D. dependent var	0.257400
S.E. of regression	0.147826	Akaike info criterion	-0.864822
Sum squared resid	1.901173	Schwarz criterion	-0.526150
Log likelihood	56.24111	Hannan-Quinn criter.	-0.727755
F-statistic	17.76310	Durbin-Watson stat	1.031602
Prob(F-statistic)	0.000000		

(vii) Robust Standard Error

Dependent Variable: TE
Method: Panel Least Squares
Date: 03/30/18 Time: 09:41
Sample: 2007 2016
Periods included: 10
Cross-sections included: 10
Total panel (balanced) observations: 100
White period standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.238205	0.230161	-1.034951	0.3036
AOH	0.000112	3.57E-05	3.138295	0.0023
IT	-0.003876	0.003372	-1.149588	0.2535
OWN	0.195463	0.092571	2.111491	0.0376
WLU	5.61E-09	2.10E-09	2.675106	0.0089

Effects Specification

Period fixed (dummy variables)

R-squared	0.736342	Mean dependent var	0.812515
Adjusted R-squared	0.696486	S.D. dependent var	0.257400
S.E. of regression	0.141807	Akaike info criterion	-0.939525
Sum squared resid	1.729389	Schwarz criterion	-0.574801
Log likelihood	60.97624	Hannan-Quinn criter.	-0.791914
F-statistic	18.47536	Durbin-Watson stat	0.823176
Prob(F-statistic)	0.000000		

Model 2

(i) POLS

Dependent Variable: TE
Method: Panel Least Squares
Date: 02/07/18 Time: 16:04
Sample: 2007 2016
Periods included: 10
Cross-sections included: 10
Total panel (balanced) observations: 100

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-8.905849	1.074005	-8.292187	0.0000
CP	-2.52E-08	1.14E-08	-2.199163	0.0303
GDP	0.882692	0.099832	8.841767	0.0000
HUB	0.336623	0.058873	5.717759	0.0000
IP	-0.002088	0.001711	-1.220586	0.2253

R-squared	0.643066	Mean dependent var	0.812515
Adjusted R-squared	0.628038	S.D. dependent var	0.257400
S.E. of regression	0.156985	Akaike info criterion	-0.816629
Sum squared resid	2.341200	Schwarz criterion	-0.686371
Log likelihood	45.83147	Hannan-Quinn criter.	-0.763911
F-statistic	42.78899	Durbin-Watson stat	0.811440
Prob(F-statistic)	0.000000		

(ii) FEM

Dependent Variable: TE
Method: Panel Least Squares
Date: 02/07/18 Time: 16:12
Sample: 2007 2016
Periods included: 10
Cross-sections included: 10
Total panel (balanced) observations: 100

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-8.479663	1.006274	-8.426796	0.0000
CP	-2.27E-08	1.04E-08	-2.190988	0.0312
GDP	0.843101	0.093458	9.021214	0.0000
HUB	0.325359	0.052862	6.154877	0.0000
IP	-0.001803	0.001531	-1.177438	0.2423

Effects Specification

Period fixed (dummy variables)

R-squared	0.742034	Mean dependent var	0.812515
Adjusted R-squared	0.703039	S.D. dependent var	0.257400
S.E. of regression	0.140268	Akaike info criterion	-0.961352
Sum squared resid	1.692051	Schwarz criterion	-0.596628
Log likelihood	62.06758	Hannan-Quinn criter.	-0.813741
F-statistic	19.02903	Durbin-Watson stat	0.834805
Prob(F-statistic)	0.000000		

(iii) REM

Dependent Variable: TE
Method: Panel EGLS (Period random effects)
Date: 02/07/18 Time: 16:17
Sample: 2007 2016
Periods included: 10
Cross-sections included: 10
Total panel (balanced) observations: 100
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-8.647078	0.988255	-8.749848	0.0000
CP	-2.37E-08	1.03E-08	-2.296029	0.0239
GDP	0.858646	0.091797	9.353716	0.0000
HUB	0.329686	0.052761	6.248661	0.0000
IP	-0.001910	0.001530	-1.247870	0.2151

Effects Specification

	S.D.	Rho
Period random	0.057876	0.1455
Idiosyncratic random	0.140268	0.8545

Weighted Statistics

R-squared	0.671482	Mean dependent var	0.494254
Adjusted R-squared	0.657650	S.D. dependent var	0.243802
S.E. of regression	0.142650	Sum squared resid	1.933164
F-statistic	48.54446	Durbin-Watson stat	0.823740
Prob(F-statistic)	0.000000		

Unweighted Statistics

R-squared	0.642839	Mean dependent var	0.812515
Sum squared resid	2.342692	Durbin-Watson stat	0.810233

(iv) LM Test (REM vs. POLS)

Lagrange multiplier (LM) test for panel data
Date: 02/07/18 Time: 16:02
Sample: 2007 2016
Total panel observations: 100
Probability in ()

Null (no rand. effect) Alternative	Cross-section One-sided	Period One-sided	Both
Breusch-Pagan	13.94250	17.15043	31.09293
	(0.0002)	(0.0000)	(0.0000)
Honda	3.733966	4.141307	5.568659
	(0.0001)	(0.0000)	(0.0000)
King-Wu	3.733966	4.141307	5.568659
	(0.0001)	(0.0000)	(0.0000)
SLM	6.313817	4.379363	--
	(0.0000)	(0.0000)	--
GHM	--	--	31.09293
	--	--	(0.0000)

(v) LR Test (FEM vs. POLS)

Redundant Fixed Effects Tests
Equation: Untitled
Test period fixed effects

Effects Test	Statistic	d.f.	Prob.
Period F	3.665951	(9,86)	0.0006
Period Chi-square	32.472209	9	0.0002

Period fixed effects test equation:
Dependent Variable: TE
Method: Panel Least Squares
Date: 02/07/18 Time: 16:14
Sample: 2007 2016
Periods included: 10
Cross-sections included: 10
Total panel (balanced) observations: 100

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-8.905849	1.074005	-8.292187	0.0000
CP	-2.52E-08	1.14E-08	-2.199163	0.0303
GDP	0.882692	0.099832	8.841767	0.0000
HUB	0.336623	0.058873	5.717759	0.0000
IP	-0.002088	0.001711	-1.220586	0.2253

R-squared	0.643066	Mean dependent var	0.812515
Adjusted R-squared	0.628038	S.D. dependent var	0.257400
S.E. of regression	0.156985	Akaike info criterion	-0.816629
Sum squared resid	2.341200	Schwarz criterion	-0.686371
Log likelihood	45.83147	Hannan-Quinn criter.	-0.763911
F-statistic	42.78899	Durbin-Watson stat	0.811440
Prob(F-statistic)	0.000000		

(vi) Hausman Test (FEM vs. REM)

Correlated Random Effects - Hausman Test
Equation: Untitled
Test period random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Period random	6.254784	4	0.1809

Period random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
CP	-0.000000	-0.000000	0.000000	0.3526
GDP	0.843101	0.858646	0.000308	0.3755
HUB	0.325359	0.329686	0.000011	0.1854
IP	-0.001803	-0.001910	0.000000	0.0607

Period random effects test equation:
Dependent Variable: TE
Method: Panel Least Squares
Date: 02/07/18 Time: 16:20
Sample: 2007 2016
Periods included: 10
Cross-sections included: 10
Total panel (balanced) observations: 100

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-8.479663	1.006274	-8.426796	0.0000
CP	-2.27E-08	1.04E-08	-2.190988	0.0312
GDP	0.843101	0.093458	9.021214	0.0000
HUB	0.325359	0.052862	6.154877	0.0000
IP	-0.001803	0.001531	-1.177438	0.2423

Effects Specification

Period fixed (dummy variables)

R-squared	0.742034	Mean dependent var	0.812515
Adjusted R-squared	0.703039	S.D. dependent var	0.257400
S.E. of regression	0.140268	Akaike info criterion	-0.961352
Sum squared resid	1.692051	Schwarz criterion	-0.596628
Log likelihood	62.06758	Hannan-Quinn criter.	-0.813741
F-statistic	19.02903	Durbin-Watson stat	0.834805
Prob(F-statistic)	0.000000		

(vii) Robust Standard Error

Dependent Variable: TE
Method: Panel EGLS (Period random effects)
Date: 03/30/18 Time: 09:39
Sample: 2007 2016
Periods included: 10
Cross-sections included: 10
Total panel (balanced) observations: 100
Swamy and Arora estimator of component variances
White period standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-8.647078	1.432193	-6.037647	0.0000
CP	-2.37E-08	7.86E-09	-3.011860	0.0033
GDP	0.858646	0.132030	6.503390	0.0000
HUB	0.329686	0.048337	6.820543	0.0000
IP	-0.001910	0.001740	-1.097599	0.2752

Effects Specification

	S.D.	Rho
Period random	0.057876	0.1455
Idiosyncratic random	0.140268	0.8545

Weighted Statistics

R-squared	0.671482	Mean dependent var	0.494254
Adjusted R-squared	0.657650	S.D. dependent var	0.243802
S.E. of regression	0.142650	Sum squared resid	1.933164
F-statistic	48.54446	Durbin-Watson stat	0.823740
Prob(F-statistic)	0.000000		

Unweighted Statistics

R-squared	0.642839	Mean dependent var	0.812515
Sum squared resid	2.342692	Durbin-Watson stat	0.810233

Model 3

(i) POLS

Dependent Variable: TE
Method: Panel Least Squares
Date: 02/09/18 Time: 12:43
Sample: 2007 2016
Periods included: 10
Cross-sections included: 10
Total panel (balanced) observations: 100

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.343796	0.437121	-7.649590	0.0000
CPXWLU	-0.071875	0.049529	-1.451169	0.1500
GDPXWLU	0.383871	0.126275	3.039959	0.0031
HUBXWLU	-4.95E-09	1.77E-09	-2.800554	0.0062
IPXWLU	-0.034449	0.039959	-0.862103	0.3908

R-squared	0.674488	Mean dependent var	0.812515
Adjusted R-squared	0.660782	S.D. dependent var	0.257400
S.E. of regression	0.149916	Akaike info criterion	-0.908778
Sum squared resid	2.135102	Schwarz criterion	-0.778520
Log likelihood	50.43892	Hannan-Quinn criter.	-0.856061
F-statistic	49.21188	Durbin-Watson stat	0.871375
Prob(F-statistic)	0.000000		

(ii) FEM

Dependent Variable: TE
Method: Panel Least Squares
Date: 02/09/18 Time: 12:49
Sample: 2007 2016
Periods included: 10
Cross-sections included: 10
Total panel (balanced) observations: 100

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.076074	0.365169	-8.423700	0.0000
CPXWLU	-0.031906	0.041800	-0.763298	0.4474
GDPXWLU	0.287391	0.106222	2.705560	0.0082
HUBXWLU	-5.52E-09	1.47E-09	-3.762288	0.0003
IPXWLU	-0.018295	0.033202	-0.551019	0.5830

Effects Specification

Period fixed (dummy variables)

R-squared	0.799034	Mean dependent var	0.812515
Adjusted R-squared	0.768655	S.D. dependent var	0.257400
S.E. of regression	0.123805	Akaike info criterion	-1.211042
Sum squared resid	1.318179	Schwarz criterion	-0.846318
Log likelihood	74.55210	Hannan-Quinn criter.	-1.063432
F-statistic	26.30250	Durbin-Watson stat	1.070564
Prob(F-statistic)	0.000000		

(iii) REM

Dependent Variable: TE
Method: Panel EGLS (Period random effects)
Date: 02/09/18 Time: 12:55
Sample: 2007 2016
Periods included: 10
Cross-sections included: 10
Total panel (balanced) observations: 100
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.138374	0.364925	-8.600044	0.0000
CPXWLU	-0.041228	0.041592	-0.991244	0.3241
GDPXWLU	0.309857	0.105773	2.929444	0.0043
HUBXWLU	-5.39E-09	1.47E-09	-3.675759	0.0004
IPXWLU	-0.022035	0.033156	-0.664582	0.5079

Effects Specification

	S.D.	Rho
Period random	0.072795	0.2569
Idiosyncratic random	0.123805	0.7431

Weighted Statistics

R-squared	0.737391	Mean dependent var	0.384857
Adjusted R-squared	0.726334	S.D. dependent var	0.240548
S.E. of regression	0.125838	Sum squared resid	1.504351
F-statistic	66.68878	Durbin-Watson stat	1.005505
Prob(F-statistic)	0.000000		

Unweighted Statistics

R-squared	0.672981	Mean dependent var	0.812515
Sum squared resid	2.144982	Durbin-Watson stat	0.869093

(iv) LM Test (REM vs. POLS)

Lagrange multiplier (LM) test for panel data
Date: 02/09/18 Time: 12:02
Sample: 2007 2016
Total panel observations: 100
Probability in ()

Null (no rand. effect) Alternative	Cross-section One-sided	Period One-sided	Both
Breusch-Pagan	1.978001	42.05511	44.03311
	(0.1596)	(0.0000)	(0.0000)
Honda	-1.406414	6.484991	3.591096
	(0.9202)	(0.0000)	(0.0002)
King-Wu	-1.406414	6.484991	3.591096
	(0.9202)	(0.0000)	(0.0002)
SLM	-0.463208	6.724111	--
	(0.6784)	(0.0000)	--
GHM	--	--	42.05511
	--	--	(0.0000)

(v) LR Test (FEM vs. POLS)

Redundant Fixed Effects Tests
Equation: Untitled
Test period fixed effects

Effects Test	Statistic	d.f.	Prob.
Period F	5.921926	(9,86)	0.0000
Period Chi-square	48.226346	9	0.0000

Period fixed effects test equation:
Dependent Variable: TE
Method: Panel Least Squares
Date: 02/09/18 Time: 12:50
Sample: 2007 2016
Periods included: 10
Cross-sections included: 10
Total panel (balanced) observations: 100

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.343796	0.437121	-7.649590	0.0000
CPXWLU	-0.071875	0.049529	-1.451169	0.1500
GDPXWLU	0.383871	0.126275	3.039959	0.0031
HUBXWLU	-4.95E-09	1.77E-09	-2.800554	0.0062
IPXWLU	-0.034449	0.039959	-0.862103	0.3908

R-squared	0.674488	Mean dependent var	0.812515
Adjusted R-squared	0.660782	S.D. dependent var	0.257400
S.E. of regression	0.149916	Akaike info criterion	-0.908778
Sum squared resid	2.135102	Schwarz criterion	-0.778520
Log likelihood	50.43892	Hannan-Quinn criter.	-0.856061
F-statistic	49.21188	Durbin-Watson stat	0.871375
Prob(F-statistic)	0.000000		

(vi) Hausman Test (FEM vs. REM)

Correlated Random Effects - Hausman Test
Equation: Untitled
Test period random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Period random	7.146137	4	0.1284

Period random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
CPXWLU	-0.031906	-0.041228	0.000017	0.0251
GDPXWLU	0.287391	0.309857	0.000095	0.0213
HUBXWLU	-0.000000	-0.000000	0.000000	0.0371
IPXWLU	-0.018295	-0.022035	0.000003	0.0331

Period random effects test equation:
Dependent Variable: TE
Method: Panel Least Squares
Date: 02/09/18 Time: 12:55
Sample: 2007 2016
Periods included: 10
Cross-sections included: 10
Total panel (balanced) observations: 100

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.076074	0.365169	-8.423700	0.0000
CPXWLU	-0.031906	0.041800	-0.763298	0.4474
GDPXWLU	0.287391	0.106222	2.705560	0.0082
HUBXWLU	-5.52E-09	1.47E-09	-3.762288	0.0003
IPXWLU	-0.018295	0.033202	-0.551019	0.5830

Effects Specification

Period fixed (dummy variables)

R-squared	0.799034	Mean dependent var	0.812515
Adjusted R-squared	0.768655	S.D. dependent var	0.257400
S.E. of regression	0.123805	Akaike info criterion	-1.211042
Sum squared resid	1.318179	Schwarz criterion	-0.846318
Log likelihood	74.55210	Hannan-Quinn criter.	-1.063432
F-statistic	26.30250	Durbin-Watson stat	1.070564
Prob(F-statistic)	0.000000		

(vii) Robust Standard Error

Dependent Variable: TE
Method: Panel EGLS (Period random effects)
Date: 04/05/18 Time: 16:15
Sample: 2007 2016
Periods included: 10
Cross-sections included: 10
Total panel (balanced) observations: 100
Swamy and Arora estimator of component variances
White period standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.138374	0.170817	-18.37268	0.0000
CPXWLU	-0.041228	0.028748	-1.434100	0.1548
GDPXWLU	0.309857	0.067427	4.595440	0.0000
HUBXWLU	-5.39E-09	6.71E-10	-8.028449	0.0000
IPXWLU	-0.022035	0.028879	-0.762993	0.4474

Effects Specification		S.D.	Rho
Period random		0.072795	0.2569
Idiosyncratic random		0.123805	0.7431

Weighted Statistics			
R-squared	0.737391	Mean dependent var	0.384857
Adjusted R-squared	0.726334	S.D. dependent var	0.240548
S.E. of regression	0.125838	Sum squared resid	1.504351
F-statistic	66.68878	Durbin-Watson stat	1.005505
Prob(F-statistic)	0.000000		

Unweighted Statistics			
R-squared	0.672981	Mean dependent var	0.812515
Sum squared resid	2.144982	Durbin-Watson stat	0.869093