Optimal Capacity Decisions of Airlines under Supply-Demand Equilibrium

A thesis submitted in fulfillment of the requirement for the degree of Doctor of Philosophy

By

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DECLARATION

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; any editorial work, paid or unpaid, carried out by a third party is acknowledged; and, ethics procedures and guidelines have been followed.

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DEDICATION

I dedicate this thesis to my beloved wife, Nayereh, for her endless support and encouragement.

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ACRONYMS

3SLS	Three- Stage Least Square Method
ABS	Australian Bureau of Statistics
Airfare /FARE	Airfare
ASIZE	Aircraft Size
ASK	Available Seat Kilometers
ASM	Available Seat Miles
ATKs	Available Ton Kilometers
ATMs	Available Ton Miles
BITRE	Bureau of Infrastructure, Transport, Cities and Regional Development
BTE	Bureau of Transport and Communication Economics
Delay	Flight Delay
DIRD	Department of Infrastructure and Regional Development
DWH	Durbin-Wu-Hausman test
EMP	Employment Rate
FAP	Fleet Assignment Problem
FE	Fixed Effects
FF/FLIGHT	Flight Frequency
HHI	Hirschman–Herfindahl Index
IV	Instrumental Variables
JFuel/ JetFuel	Jet fuel cost
LCC	Low-Cost Carriers
LF	load factor
LowTemp	Minimum Temperature
MES	Minimum Eigenvalue Statistics
MLE	Maximum likelihood estimator
MSE	Mean Square Error
NLP	Non-Linear programming
OD	Origin-Destination
OF	Objective Function
OLS	Ordinary Linear Regression Model
PASS	Number of Passengers/ Passenger Demand/ Air Passenger
POP	Population
Rain	Average Monthly Rain
RE	Random Effects
SDE	Supply-Demand Equilibrium

SEATS	Total Available Seats
SEM	Structural Equation Modeling
SUR	Seemingly Unrelated Regression
TSLS	Two-Stage Least Square Method

ABSTRACT

In the last three decades, airlines across the globe have experienced significant incidents and milestones such economic recessions, de-regulations, and jet fuel fluctuations, leading to many consolidations and even bankruptcies. Airlines seem to have a few options to respond to these disruptions and fluctuations. Capacity planning is one of the key tools that airlines apply to manage air traffic demand and their operating costs. As such, the carriers may alter the number of flights, use different types of airplanes, upgrade the seats in the aircraft, and even increase the load factor to maintain their market share and profitability, which can occasionally lead to passenger dissatisfaction. 'Capacity Planning' is defined in this research as a combination of the number of flights and aircraft size that airlines choose to manage traffic demand on a given origin-destination route. It affects the airlines' service quality and operating costs, in turn, influencing their market share and profitability. Capacity planning has become more important for airlines due to the diminishing relative significance of traditional tools such as airfare management or hedging contracts.

However, capacity planning seems to be a difficult decision-making task for airlines as they need to consider many factors on both sides of the supply-demand equilibrium of the flight market and different limitations such as access to specific aircrafts, airports, or even flight regulations. Any changes in the capacity would trigger a sophisticated set of interrelated changes in passenger demand, flight frequency, aircraft size, airfare, and flight delay, finally leading to an equilibrium shift. This statement considers economies of density that means, given no congestion, more density in terms of higher

passenger demand leads to more plane-miles by either more flights or larger aircrafts. In fact, with no capacity constraints, there is an ongoing loop causing higher density from the demand side and more plane-miles from the supply side of the flight equilibrium. However, this picture is no longer valid once the capacity constraint is added to the equilibrium. Capacity constraint introduces a new player, flight delay, to the equilibrium. In other words, higher density leads to more flight delays because of capacity constraints. Flight delays bring extra costs to airlines, diminishing economies of density. Therefore, airlines need to consider all these interrelated interactions to make efficient capacity plans on their operating networks.

This thesis develops an optimisation model to assist airlines to make the optimum capacity decisions for individual routes of a given market such as a specific airport or network to maximise the potential passenger demand under the flight supply-demand equilibrium. To address this research, three key questions are identified as follows: What are the key determinants of airlines' capacity decisions under the supply-demand equilibrium of flight market? How does an airline's capacity decision influence flight delays? How can airline capacity decisions be optimised for the individual routes of a given market to maximise the total potential flight demand with respect to the market's capacity constraints? Furthermore, this research answers some significant questions related to the interactions among the key players of the supply-demand equilibrium of the flight market.

To answer these questions, this research is implemented in three steps. In the first step, the key drivers of capacity planning and demand modelling are statistically identified on both sides of the supply-demand equilibrium by applying the two-stage least square technique on the time-series cross-sectional data of 21 major routes of the Australian domestic market. In the second step, the impact of changes in the elements of capacity decisions in flight delay are investigated by using the Hausman-Taylor regression technique on the Australian domestic data. By connecting the findings of step 1 and 2, a research framework is created to be used as the basis of the optimisation algorithm in the final step. The model is developed by the inclusion of a series of exogenous and endogenous factors under the supply-demand equilibrium. To address the simultaneity among the variables, a system of four non-linear equations, flight demand, flight frequency, aircraft size, and flight delay, is developed and estimated individually by two statistical simultaneous techniques – three-stage least square technique (3SLS) and maximum likelihood estimator (MLE). The data of seven Australian domestic routes, linking Melbourne to other major cities in Australia, was applied, as the case study, to estimate the model's coefficients. Finally, the non-linear optimisation technique was applied to the estimates of 3SLS and MLE separately to find the optimum capacity plan of the given routes. All proposed models were verified and tested in different steps. As the key contribution, this thesis proposes an optimisation model based on a system of non-linear equations of the flight supply-demand equilibrium to maximise the potential flight demand of a given market with respect to the market's capacity constraints. This model is based on the theory of economies of density and applied the time-series cross-sectional data of flight market to empirically estimate the coefficients of passenger demand equation as the objective function. Compared to other models of capacity planning that generally contain a relatively a short list of micro-level factors in modelling, the proposed model contains all required macro- and micro-level factors.

As the key contribution, this thesis highlights the key drivers of capacity planning and demand modeling of supply-demand equilibrium and their relationships in the Australian flight domestic market. As a part of results, there is a bilateral relation among the elements of capacity decisions and passenger demand. The results statistically differentiate the airlines' policies of capacity planning across the different markets. The results suggest that a higher demand for flights primarily results in increased flight frequency rather than increased aircraft size or load factor. The load factor is identified to be an insignificant variable in capacity planning of the airlines. Competition between airlines, participation of low-cost carriers, and jet fuel expenses are thought to influence airlines' capacity decisions, albeit differently across the given markets. Interestingly, jet fuel cost inflations stimulate the flight demand in the short-haul market as well as the routes linking the major cities to the industrial ones. The socio-economic parameters of population and employment rates affect the flight demand in the different markets in different ways. The findings indicate the airlines' capacity decisions influence flight delays. The results indicate that more frequent flights and larger aircrafts together are associated with more flight delays. Route congestion is caused by more flights, albeit to a higher degree for low-cost carriers. Jet fuel cost inflation is expected to cause flight delays, but more for the legacy airlines than low-cost carriers.

From the results of the optimisation model, for a given period, December 2015, the optimum solutions of 3SLS and MLE indicate, respectively, a 1.72% and 0.66% improvement on the flight demand compared to the reported actual plan for the airlines. The estimated MSE of the MLE model is smaller than that of 3SLS; however, estimated coefficients of 3SLS are statistically more significant than those of MLE, resulting in more practical results in the optimisation section. The proposed model and findings of this thesis can potentially be applied by airlines as well as policy makers to fleet planning and airport infrastructure development projects in different airports and hub-and-spoke networks across the globe. The proposed optimisation model may be enhanced by using the theory of full equilibrium to develop the optimisation model through adding the factors of the other transportation modes. Due to the data limitation, airfare was only applied as an exogenous parameter in the passenger demand equation of the optimisation model. Airfare can potentially be upgraded to become a key variable of airline capacity planning under the supply-demand equilibrium. In future research, the data of individual airlines can be applied separately at the route level. With the airline dimension in modelling, further explorations can be done on the airline's policies and performance of capacity planning in different markets. The proposed model can potentially be applied to other airports and hub-and-spoke networks across the globe which it surely leads to further explorations about the airlines' policies and capacity planning as well as the demand modelling under the supply-demand equilibrium.

Keywords: Aviation, Capacity planning, Supply-demand equilibrium, Econometric Analysis, optimization

Chapter 1

Introduction

1.1. Introduction

Airlines are seeking to keep their core competencies to adequate standards through competitive service quality and airfares to control market share and the level of profitability. For this purpose, capacity decision is one of the primary tools that airlines rely on to manage and control air traffic demand and airfares (Wei and Hansen, 2005; Carey, 2015). As such, carriers may alter the number of flights, use different types of airplanes, upgrade the seats in the airplane, and even increase the load factor to maintain their market share and profitability, which occasionally results in customer dissatisfaction (Stock, 2013). Capacity decisions combined with traditional approaches such as the control of airfares and hedging contracts have historically been used by airlines to mitigate the risk of bankruptcy arising from unexpected events such as the 9/11 attacks, 2008 global financial crisis, and oil price surge in 2008 (Wei and Hansen, 2005; Purnanandam, 2008).

The role of capacity decisions in airline profitability is expected to become more significant because of the diminishing relative effect of other airline tools such as airfare increase or hedging contracts (Mohammadian et al., 2019a). Similar to the other tools, capacity planning seems to be challenging for airlines as they need to consider many factors on both sides of the supply-demand equilibrium of the flight market and include different limitations such as their access to the number and types of aircrafts, airports, or even flight regulations. As discussed by Zou and Hansen (2012), any change in the capacity would trigger a sophisticated set of interrelated changes in passenger demand, flight frequency, aircraft size, airfare, and flight delay finally leading to an equilibrium shift.

This statement takes into account economies of density that means, given no congestion, more density in terms of higher passenger demand leads to more plane-miles by either more flights or larger aircrafts. Airlines operate larger aircrafts as it results in lower operating costs per seat, and they can offer lower fares to passengers. Cheaper fares stimulate flight demand leading to higher density. Therefore, with no capacity constraints, there is an ongoing loop causing higher density from the demand side and more plan-miles from the supply side of the flight equilibrium (Zou and Hansen, 2012). However, this picture is no longer valid once the capacity constraint is added to the equilibrium. Capacity constraint introduces a new player, flight delay, to the equilibrium. In other words, higher density leads to more flight delays because of capacity constraints. Flight delays bring extra costs to airlines, diminishing economies of density. In fact, higher flight delay leads to low passenger demand either directly or indirectly as an outcome of airline responses. Figure 1.1 describes these interactions under the supply-demand equilibrium of the flight market.

Therefore, airlines need to take into account all these interrelated interactions to design efficient capacity plans on their operating networks. In fact, an airline should decide continuously about flight frequency and aircraft type for each individual route of its operating network to maximise its market share and profitability. These airline decisions must consider capacity constraints in terms of airport or fleet access. An airline needs to ensure its capacity planning effectively controls its operating costs and must manage its market share with a precise look at other competitors. In the aviation industry, the key interest is to know the priorities of airport expansion to bring the highest benefits in terms of more flight demand across the whole market. To make such these decisions, governors or investors need to consider the elasticity of passenger demand to the capacity changes in addition to the other factors stimulating demand such as socio-economic factors or airfares

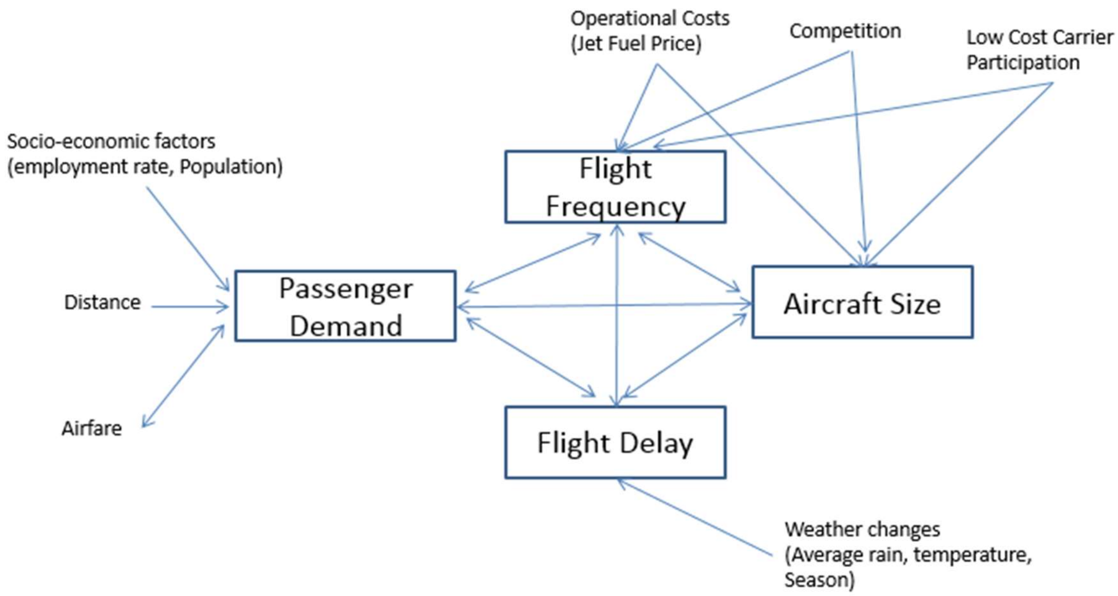

Figure 1.1 Key drivers of the supply-demand equilibrium of flight market

1.2. Aims and questions

This study aims to develop an optimisation model of capacity decisions that considers all key drivers on both sides of the supply-demand equilibrium. It is significant to emphasise that the level of capacity decisions being targeted in this study is at the strategic level, which is different from airline decisions on flight frequency and aircraft choice at the tactical or operational level. The airline's planning on tactical or operational levels is addressed as "fleet planning" or "fleet assignment" in the aviation industry (Wei and Hansen, 2007). Airlines' strategic planning of flight frequency or aircraft size is influenced by their long-term policies related to business core strategies, infrastructure development, and government regulations. Therefore, the airlines' strategic planning is categorised as long-term decisions, compared to the tactical and operations planning which are known as short-term or even daily decisions. At the tactical level, airlines consider factors including fleet commonality, network structure, and purchase price to make capacity decisions such as new aircraft acquisition through a function named 'fleet planning'.

At the operational level, airlines make daily decisions about flight frequency and choice of aircraft, which needs to be allocated to a market or a route, normally through a function named 'fleet assignment'. Most airlines apply some computer packages at the operational level, based on mathematical programming models. These models primarily comprise a profit-maximisation objective function and a set of constraints for aircraft availability. Therefore, these levels of planning assist airlines in daily capacity planning on their routing network.

Airlines' capacity planning at tactical and operational levels are always influenced by capacity decisions at the strategic level, and this study aims to explore this phenomenon. The strategic decisions are usually made at the same time and have an interrelated relationship with airlines' decisions on networking structure. Strategic capacity planning assists airlines in making decisions about strategical changes in their operating networks such as adding a new operating route, applying the hub-and-spoke network instead of point-to-point service, or sizing up the average aircraft on a specific route in the long run to meet the growing passenger demand (Wei and Hansen, 2007).

As indicated above, the primary objective of this research is to develop an optimisation model of the airlines' capacity planning by considering all key drivers on both sides of the supply-demand equilibrium of the flight market. Therefore, the main question of this study is "How can airlines optimise their capacity decisions under the air supply-demand equilibrium to maximise the potential passenger demand?"

This primary question can be broken down into the following three research questions:

***RQ1*: What are the key determinants of airlines' capacity decisions under the supply-demand equilibrium of flight market?**

This research question comprises the identification of the antecedents of capacity decisions in the airline industry as well as examination of the factors on both sides of the supply-demand equilibrium of the flight market.

The research question 1 comprises the below sub-questions:

> *Sub-RQ1.1:* Are airlines' capacity strategies different for short- and long-haul routes? If so, what factors drive these strategies?
>
> *Sub-RQ1.2*: How do the supply side parameters, including competition, participation of low-cost carriers, and jet fuel cost inflation, affect passenger demand?
>
> *Sub-RQ1.3*: How do the demand-related factors influence the airlines' capacity decisions?

Econometric techniques were applied to statistically investigate the key parameters on both sides of the demand-supply equilibrium of the aviation industry to identify key drivers in the airlines' capacity decisions.

***RQ2*: How does an airline's capacity decision influence flight delays?**

Flight delay is known as one of the key determinants of capacity decisions in the supply-demand equilibrium, and it is a key driver of an airline's capacity decisions according to the economy of density. The research question 2 is to investigate the key drivers on flight delay in an endeavour to highlight the impact of airlines' operations on flight delay. As a part of research question 2, the three sub-questions below are answered:

Sub-RQ2.1: How do the elements of capacity decision influence flight delay?

Sub-RQ2.2: How do airline-related and route-related factors influence flight delay?

Sub-RQ2.3: How do airlines' policy and performance affect flight delay?

As the dataset is categorized as time-series cross-sectional data, the econometric techniques of panel data analyses were chosen to be applied in this step. However, the bilateral relation among some of the variables influences the final model selection. The first two research questions (RQ1 and RQ2) are prerequisite to address RQ3 as the main key question of this thesis.

***RQ3*: How can airline capacity decisions be optimised for the individual routes of a given market to maximise the total potential flight demand with respect to the market's capacity constraints?**

RQ3 is to propose an optimisation model to identify the optimum capacity decisions of airlines in origin-destination routes to maximise the potential passenger demand. The following sub-question are answered in this step:

> *Sub-RQ3.1:* How do airlines 'capacity decisions and flight delay along with the other drivers stimulate flight demand?

The optimisation model is aimed to reflect all routes and network/airport constraints in modelling. Furthermore, the effect of simultaneity and endogeneity among the variables must be considered to develop the model. The econometric techniques, known as structural simultaneous equations model, are applied in model development. The non-linear optimisation technique is applied at the final step to find the optimum solution.

1.3. Research Methodology

The primary objectives of this research are to investigate the key drivers of the supply-demand equilibrium of the flight market and develop an optimisation model of airlines' capacity decisions. To fulfil objectives 1 and 2, described in Section 1.2, this study needs to empirically investigate the supply-demand equilibrium of the flight market to identify the key drivers of the airlines' capacity planning, of demand modelling, and of flight delay. Therefore, one of the key steps of this study is to identify the significance of the relationships among the model's factors; these relationships are defined as the research hypotheses.

The theoretical background of this research is defined by the findings of the literature review. Therefore, this research is categorized as adopting a positivist paradigm; it aims to test a theory through observations. This research is aimed to analyse the factors of supply-demand equilibrium of the flight market (Black et al., 2012), independently from prices and quantities of transportation substitutes such as surface transportation, vehicles, and trains. Therefore, this study is categorised under the theory of partial equilibrium.

The deductive approach is considered here because the relationships among the model parameters, defined as the model's hypotheses, are investigated by implementing a survey on the monthly data of the domestic flight market of Australia. The dataset is categorised as time-series cross-sectional data. The data is adjusted seasonally to offset the impact of a season's changes on the models, and outlier test analysis is applied to identify outliers and remove them from the dataset.

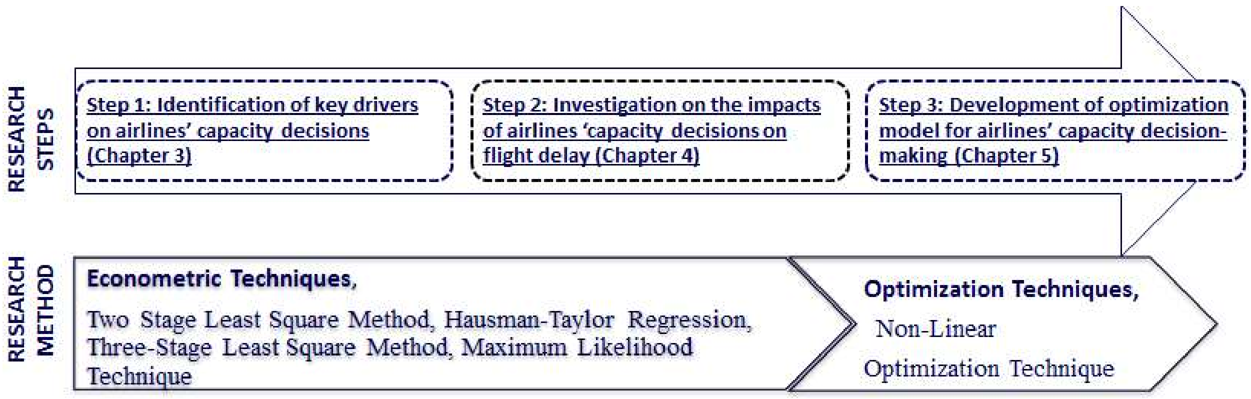

Figure 1.2 Research Steps/methods

The econometric techniques are applied in the first and second steps of this study to investigate the key drivers of demand modelling and capacity planning and their relationships under the supply-demand equilibrium of the flight market. However, as it is discussed in Chapter 3, on applying the Durbin-Wu-Hausman test, we can find bilateral relations among the variables on both sides of the demand-supply equilibrium. Therefore, the application of the ordinary least square methods results in biased and systematic errors. To avoid the biased results, the econometrical techniques categorised as instrumental variables estimators are applied in modelling to estimate the model's coefficients. These techniques include single model techniques, such as two-stages least square method (TSLS) or Hausman Taylor regression estimator, or full system simultaneous techniques such as three-stage least square method or maximum likelihood estimator (MLE). The model's estimation is verified by variance inflation factor to check significant multicollinearity problems (Hair et al., 2006).

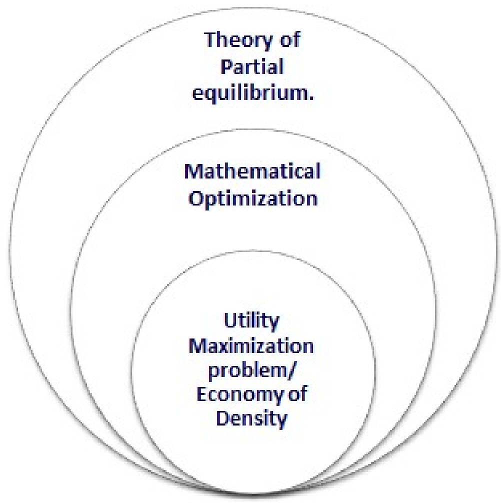

Figure 1.3 Research theoretical frameworks

As the last step, this study aims to develop an optimisation model for airline capacity planning under the supply-demand equilibrium of the flight market. The model objective is to maximise passenger demand in conjunction with the theory of economy of density, as briefly described in section1.1.

According to the theory of economies of density, higher densities of populations allow synergies in service provision leading to lower generalised costs for customers. In the aviation industry, given no congestion, more density leads to more plane-miles either by more flights or larger aircraft size. More flights may improve the quality of service to customers, and by using larger aircrafts, airlines may reduce the operating costs that finally result in less air fare for customers. However, higher density, given no congestion, reduces the generalised costs for customers. However, with congestion, delay occurs due to capacity restriction. Lengthening flight time leads in extra costs to airlines, thus offsetting or reversing economies of density.

Table 1.1 summarises the research design with respect to the research objectives and executive steps.

Table 1.1 Research Methodology

Research Design	Research Selection	Reason for Choosing the Item
Paradigm	Positivist	To test the theory (Economy of Density) through observation
Theory	Theory of Partial Equilibrium	To analyse the supply-demand equilibrium of flight market, independently of other transportations
	Theory of Economies of Density	To map the interactions among the model parameters
Approach	Deductive	To develop hypotheses on the relation among the factors using existing theories from the literature
Strategy	Case study	To test the theory by analysing the prior data in the targeted market
Primary Method	Quantitative	The research factors are categorised as quantitative data
Secondary Method	Instrumental variable estimators (Step 1 & 2)	To offset the endogeneity between parameters
	Structural simultaneous equations model and non-linear optimisation (Step3)	To estimate the optimum coefficients of the capacity model with respect to the simultaneity and non-linear relations among the variables
Data Collection	Secondary data	Considerable number of observations required to make the estimation
Data Specification	Time-series, cross-sectional	To analyse the information on the Australian domestic flight market
Data Verification	Outlier analysis	To identify outliners and remove them from the dataset
	Durbin-Wu-Hausman test Hausman Specification test	To verify the endogeneity and simultaneity among the model's parameters
Model Estimation Verification	Variance inflation factor comparative model development (Step 2 &3)	To check significant multicollinearity problems and compare and validate the model estimations

1.4. Research Data

The research applies the data of the Australian domestic market relating to the routes among the states of Adelaide, Melbourne, Sydney, Perth, Darwin, Hobart, Canberra, and Brisbane. Figure 1.3 presents the routes that were targeted in this research and the monthly data from January 2004 to

December 2015. This market was chosen due to the availability of historical data of the different demand- and airline-related variables used in this research. This market was a good and reliable sample of the Australian domestic market. The dataset contains the data of four dominant airlines, Qantas, Virgin, Jetstar, Tigerair, and other carriers that participated during this period, namely QantasLink, Regional Express, Virgin Australia - ATR/F100 Operations, and Virgin Australia Regional Airlines.

Figure 1.4 Targeted Domestic Origin-Destination Flight Routes[1]

1.5. Significance and impact of the study

With respect to the predetermined steps of this study, the expected findings can be significant in different ways:

- This study exclusively initiates the supply-demand equilibrium of the flight market and investigates the relation among the parameters on both sides of the equilibrium. As the

[1]This plot is chosen based on the information of the Domestic Aviation Activity Reports - Department of Infrastructure and Regional Development (http://bitre.gov.au/).

expected results, this research reveals the new drivers in capacity modelling as well as demand modelling and the new relations among the factors. The findings can effectively be applicable to the different stakeholders of the aviation industry such as airlines, airport investors, and even regulators.

- The prior studies primarily addressed the flight markets of the US or Europe, which are geographically and economically different from Australia. This study is aimed to explore the determinants that drive the supply-demand equilibrium on the level of the origin-destination routes and the parameters that influence the capacity decisions of the dominant carriers in the Australian domestic market.
- The proposed optimisation model of this study can effectively be applied to assist airlines in capacity planning. It also can potentially be applied for decision making in the capacity development of the airports or networks.

1.6. Thesis Structure

This thesis is organised in six chapters, designed to address the main objective and associated research questions, as indicated in section 1.2. This chapter introduced the research topic, set out the research objective and questions. Regarding the research questions, the chapter presented the research methodology, outlined the research structure and highlighted the significance and impact of the research. The subsequent chapters are described as below.

Chapter 2 is a comprehensive literature review to the research topic of the airline's capacity planning under supply-demand equilibrium of the flight market. It discusses the concept of passenger demand modelling and airline's capacity planning in the context of air supply-demand equilibrium. It provides a review on the key determinants of airline's capacity planning, passenger demand, flight delay, and air supply-demand equilibrium. It also discusses the prior studies of airlines capacity modelling in the context of air supply-demand equilibrium. Chapter 2 summarise the current literature to identify the gap in the extant knowledge.

Chapter 3 focuses on answering the first research question that is *What are the key determinants of airlines' capacity decisions under the supply-demand equilibrium of flight market?* The chapter develops an econometric model, based on two- stage least square technique, to identify the key drivers of airlines capacity planning under supply-demand equilibrium of the flight market. The data of the major routes of Australian domestic market is applied as the research case study in this chapter. Regarding the outputs of statistical analyses, the chapter discusses the determinants of passenger demand as well as the key drivers of airlines' strategies of capacity planning in the domestic flight market.

Chapter 4 aims to answer the second question that is *How does an airline's capacity decision influence flight delays?* This chapter identifies the key determinants on flight delay as one of the key players of supply-demand equilibrium of the flight market. This chapter describes the flight delay phenomenon, and its status in Australian domestic flight market. It provides the model parameters and discusses the methodological framework in terms of model specification, proposed technique, and model formulation. This chapter formulates the flight delay based on the Hausman and Taylor's instrumental variables estimator and discusses the findings relating to the impact of flight delay on passenger demand and airlines' strategies of capacity planning.

Chapter 5 addresses the key objective of this research that is to develop an optimisation model of capacity planning under air supply-demand equilibrium for a given network or airport. The model assumptions, parameters and variables, and objective function are described in this chapter. Then, the two econometrical techniques, three-stage least square method (3SLS) and Maximum likelihood estimation (MLE), are separately applied to estimate the coefficients of the objective function. The models are formulated based on the non-linear optimisation technique, then the optimal solutions are compared and discussed. This chapter answers the final question that is *How can airline capacity decisions be optimised for the individual routes of a given market to maximise the total potential flight demand with respect to the market's capacity constraints?*

Chapter 6 presents the thesis conclusions and discusses the potential implications of the key research findings for airlines' capacity planning. The research questions, indicated earlier in this chapter, are revisited to assess whether they are sufficiently addressed. The chapter highlights the key contributions of this research and the practical implications. It also provides some directions to the future research, along with research limitations.

1.7. Summary

This chapter has developed the research context. It has discussed the rational for undertaking this research and described the research objective and key questions. It has introduced the methodological framework and described the research structure.

This thesis is important to developing an optimisation model for airlines' capacity planning considering the key drivers on the both sides of supply-demand equilibrium of the flight market. The statistical techniques are applied within the thesis to identify the relationships among the parameters and variables in the context of either passenger demand modelling or capacity planning. The research applies the non-linear optimisation technique to develop the proposed model of airlines' capacity planning. The time-series cross-sectional data belonged to the major routes of the Australian domestic flight market are applied as the thesis case study to evaluate the econometrical models as well as verify the proposed optimisation model of airlines' capacity planning. The research aims to reveal the important findings relating the key determinants of supply-demand equilibrium of Australian domestic flight market. The proposed optimisation model can practically be applied for airlines' capacity planning for the individual routes of hub-and-spoke networks or airports across the globe.

Chapter 2

Literature Review

2.1. Introduction

This chapter defines the concept of passenger demand, capacity planning, air supply-demand equilibrium, and flight delay. It provides a review on the key drivers of airline's capacity planning, passenger demand, flight delay, and air supply-demand equilibrium. The section begins by an introduction on airlines' capacity planning. The passenger demand is known as the key driver of airlines capacity planning. As a result, it also provides a review on the key determinants of passenger demand. Flight delay is another player of capacity planning under supply-demand equilibrium as discussed in Chapter 1. The antecedence of flight delay is also discussed in this section. It then discusses the prior studies of airlines capacity modeling, particularly the ones are developed under air supply-demand equilibrium. The final section of literature review provides a summary review of the existing capacity planning models and identifies gaps in the current literature review.

2.2. Air capacity planning

According to Gold (1955) capacity can be defined in two forms; a) "as an estimate of the total amount which can be produced of any given product, assuming some specified allocation of plant facilities to such output" and b) "as an estimate of the composite productive capacity covering some specified range of products". The first definition can be stated in physical terms and applied to assess the capacity volume as well as its relative changes. This definition assumed that there is a sufficient access to materials, labour and other inputs to fully utilise of current capital facilities. An airline's capacity can be defined according to the first definition. Therefore, air supply can address the willingness and ability of an airline to provide a specific number of seats at a given airfare, and time period. The air supply can be expressed in available seat miles/kilometers (ASMs/ASKs) or available ton miles/Kilometers (ATMs/ATKs) (Vasigh et al., 2013). Capacity is defined in this study as total available seat mile calculated by multiplying all two-way non-stop flights between origin and destination, and average aircraft size for a given route and time period.

Capacity planning is a major challenge that airlines encounter on the flight routes of their service networks. Capacity decisions affect flight services in terms of cost and quality that in turn influence the flight demands of the different groups of passengers, such as price- or time-sensitivity (Hsu and Wen, 2003). Capacity planning in general aims to determine the fleet size in terms of number of flights, choice of aircrafts, network characteristics as well as average fares for a given operational environment, and time period. Macro capacity planning is known as one of the most popular approaches, where passengers demand of a given network or airport is applied as the key driver of determination of the required numbers of aircrafts in different types. However, macro-capacity planning generally oversimplifies the practical environment which it makes hard to address the adaptability of a specific choice of aircraft flying on a given route. To keep the needed granularity, micro-fleet planning comes after macro-capacity planning to reflect the required details of a daily airline operation management (Wang et al. 2015). Micro-fleet planning is known as the fleet assignment problem (FAP) within the literature body. FAP deals with the choice of aircrafts to the scheduled flights, with respect to equipment capabilities and availabilities, operational expenses, and potential revenues. Assigning the larger aircrafts than size required for a flight leads in unsold seats, which in turn results in higher operational costs. By contrast, the allocation of smaller aircraft than needed on a flight would lead in lost customers because of insufficient capacity. Therefore, FAP constitutes a necessary part of an airline scheduling process (Sherali et al. 2006).

In this study, *Capacity Planning* is categorized in macro level, and defined as a combination of the number of flights and average aircraft size that airlines choose to manage their traffic demand on a given origin-destination route. These decisions are prerequisites for planning of an airline's operation, such as flight scheduling and crew assignment (Hsu and Wen, 2000). Airlines invariably attempt to maximise profit by increasing their market share and reducing their fixed and variable costs. However, the modeling of the air capacity planning is complex (Teodorovic and Krcmar-Nozic, 1989). An over-large fleet size would lead to unnecessary operating expenses for airlines due to the increasing capital assets. By contrast, an underestimated fleet size may result in losing a number of passengers in the benefits of other competitors. Furthermore, airlines across the globe inevitably must have pursued a high-cost and low-fare policy which it pressured their profit margins. Therefore, airlines always investigate to find a more practical capacity planning to meet passenger demand with lower expenses (Wang et al. 2015). In other words, airlines need to pursue the ideal strategy to find the correct number of seats at the right price. The right number of seats can be addressed by the fleet assignment process, and a right price can be achieved by yield or revenue management (Sherali et al. 2006).

On the supply side of the flight market equilibrium, studies largely addressed network modeling, hub-location problems, and the determination of flight frequency and aircraft size (e.g., Hansen and Kanafani, 1989; Teodorovic and Krcmar-Nozic, 1989; Jaillet et al., 1996; Hsu and Wen, 2000; Saberi and Mahmassani, 2013). Prior studies attempted to simultaneously or individually determine flight frequency, choice of aircraft size, and even load factor (e.g., Givoni and Rietveld, 2010; Hsu and Wen, 2003; Pitfield et al., 2010; Teodorovic and Krcmar-Nozic, 1989; Zou and Hansen, 2012). prior studies primary addressed the capacity planning of airlines in terms of the determination of optimum flight frequency (e.g., Hsu and Wen, 2003). However, some studies considered aircraft size and load factor as additional factors in capacity decisions during the modeling of capacity (e.g., Pitfield et al., 2010). Without considering all aspects of an airline's capacity planning, which includes flight frequency, aircraft size, and load factor in an integrated model, it is difficult to visualize a holistic picture of airline strategies for capacity decisions.

Capacity planning also affects air passenger demand. Prior studies highlighted the econometric impact of airlines capacity planning on passenger demand (e.g., Wei and Hansen, 2005; Wei and Hansen, 2006; Wang et al., 2014). Wei and Hansen (2005, 2006) applied econometric models in the U.S. market and argued that airlines could realise higher passenger demand by offering more flights rather than utilizing larger aircrafts in the non-stop duopoly markets, and hub-and-spoke networks. Wang et al. (2014), through an empirical study of the Chinese domestic flight market, suggested that airlines can accommodate rapid demand growth by adding more flights, while flying larger aircrafts also contribute to market expansion.

2.3. Air passenger demand modeling

According to Vasigh et al. (2013, p. 46), Demand is defined "*as the ability and willingness to buy specific quantities of a good or a service at alternative prices in a given time period under ceteris paribus conditions* ".Understanding the theory and function of demand is one of the significant aspects for any business, because the demand characteristics determines the patterns and specifications of supply. In the aviation industry, demand is frequently expressed in terms of number of passengers (PASS), revenue passenger miles/kilometers (RPMs/ RPKs) which it normalises passenger demand based on the miles/ kilometers travelled, and revenue ton miles/kilometres (RTMs/RTKs). Number of passengers (PASS) is applied in this study to address passenger demand. A demand modelling is to develop the functional relationship between the quantity demanded and factors driving demand.

Air transportation is known as one of the most networked travel systems comprising the markets in different levels of performance, growth and volatility. Demand modeling and forecasting is one of the critical topics of air transportation industry. Airlines need to know the specifications of passenger demand for the purposes of revenue management and capacity planning (Swan, 2002). Airlines should recognise that the factors stimulating passenger demand are influenced not only by airfares but also by the many attributes that comprise the quality of service (Alamdari and Black, 1992). The study on the determinants of the passenger demand has been one of the primary research interests in the aviation industry since the 1950's (Harvey, 1951). Harvey first studied the antecedents of passenger demand patterns across the U.S. According to Harvey, population, distance, and geographic distribution of large metropolitans are among the primary drivers of the air traffic demand patterns. Prior studies on air passenger demand developed models either as a function of the factors of the quality of service (e.g., Pitfield et al., 2010), socio-economic and demographics (e.g., Grosche et al., 2007), or a combination of factors from both groups (e.g., Abraham, 1983; Fridstorom and Thune-Larsen, 1989; Jorge-Calderón, 1997; Wei and Hansen, 2006).

Passenger demand may comprise either inelastic (Hansen and Kanafani, 1989; Teodorovic and Krcmar-Nozic, 1989; Hsu and Wen, 2000; Adler, 2001) or endogenous variables (e.g., Hsu and Wen, 2003; Pitfield et al., 2010). However, passenger demand seems to be elastic to the changes in capacity decisions with respect to competition in air transportation (Hsu and Wen, 2003).

For example, Fridstorom and Thune-Larsen (1989) modeled the air traffic of the Norwegian network, highlighting traffic flow, fares, travel time, income, and population as factors in their model. Jorge-Calderón (1997) developed a demand model to examine the entire network of European routes to identify the key drivers in that market. Jorge-Calderón identified two categories in flight-demand modeling: (1) geo-economic factors and (2) service-related factors. The first category includes the exogenous measures such as income, distance, and population. The second category, the service-related factors, comprises the airfare and quality of service, controllable by the airlines. Jorge-Calderón (1997) suggests flight frequency, aircraft size, and load factor as the determinants of the quality of airline service and shows that flight frequency and aircraft size are significant for shorter routes and the longer routes, respectively. Wei and Hansen (2006) developed an econometric model for the hub-and-spoke network in the U.S. market, investigating the roles of lowering ticket prices and increasing airport acceptance in stimulating the number of connecting passengers in a network. They considered the service quality parameters, flight frequency, aircraft size, and ticket price in addition to the socio-economic factors to develop their demand model. Their findings showed that increasing flight frequency affects the demand of connecting passengers more strongly than aircraft size.

Several recent studies evaluated the effect of unexpected events such as the Gulf War in 1991, the tragedy of September 11, 2001, the Iraq War in 2003, and the global recession of 2008 on market demand. Unsurprisingly, those studies revealed that the occurrence of such events sharply reduced air-travel demand in both the long and short terms (Chi and Baek, 2013; Ito and Lee, 2005; Franke and John, 2011). The studies also stressed that the demand frameworks would depend on airline strategy (full-service vs. low-cost) and airport competition (Barrett, 2004; Pitfield et al., 2010).

The prior studies also investigated the impact of environmental factors on airlines' capacity planning. For example, Bruekner and Zhang (2010) investigated on the impact of airline emissions charges on airline service quality, the features of aircraft design, and network structure as well as airfares. They developed a profit-maximization problem based on a detailed theoretical model of competing duopoly airlines and applied that on an aggregate data for all the world's airlines. Their findings indicate the emission charges results in higher air fares, less flight frequency, and raises aircraft fuel efficiency with no effect on aircraft size.

2.4. Supply-demand equilibrium of the flight market

Supply-demand equilibrium of air market would occur when both sides of equilibrium agree on an airfare which it determine the allocation of available seats. At equilibrium, the quantity demanded is the same as quantity supplied. In another word, supply-demand equilibrium of air market is the setting of airfare such that the demand of seats and available seats provided by airline are exactly equal. Airlines always want to achieve high ticket prices to maximise their revenues, by contrast, passengers always seek the desire low airfares to minimise their traveling costs. Airlines always need to estimate passenger demand and make capacity planning and ticket pricing with respect to their demand estimations (Vasigh et al., 2013). Underestimating passenger demand causes an airline to offer relatively lower airfares to customers (Figure 2.1, Area 1). In this scenario, passenger demand is greater that the available seats provided by airline. Therefore, airline is unable to meet passenger demand, and may lose the market share in the benefit of the other competitors. Furthermore, an airline is unable to sufficiently benefit from the market due to offering the relatively low airfare.

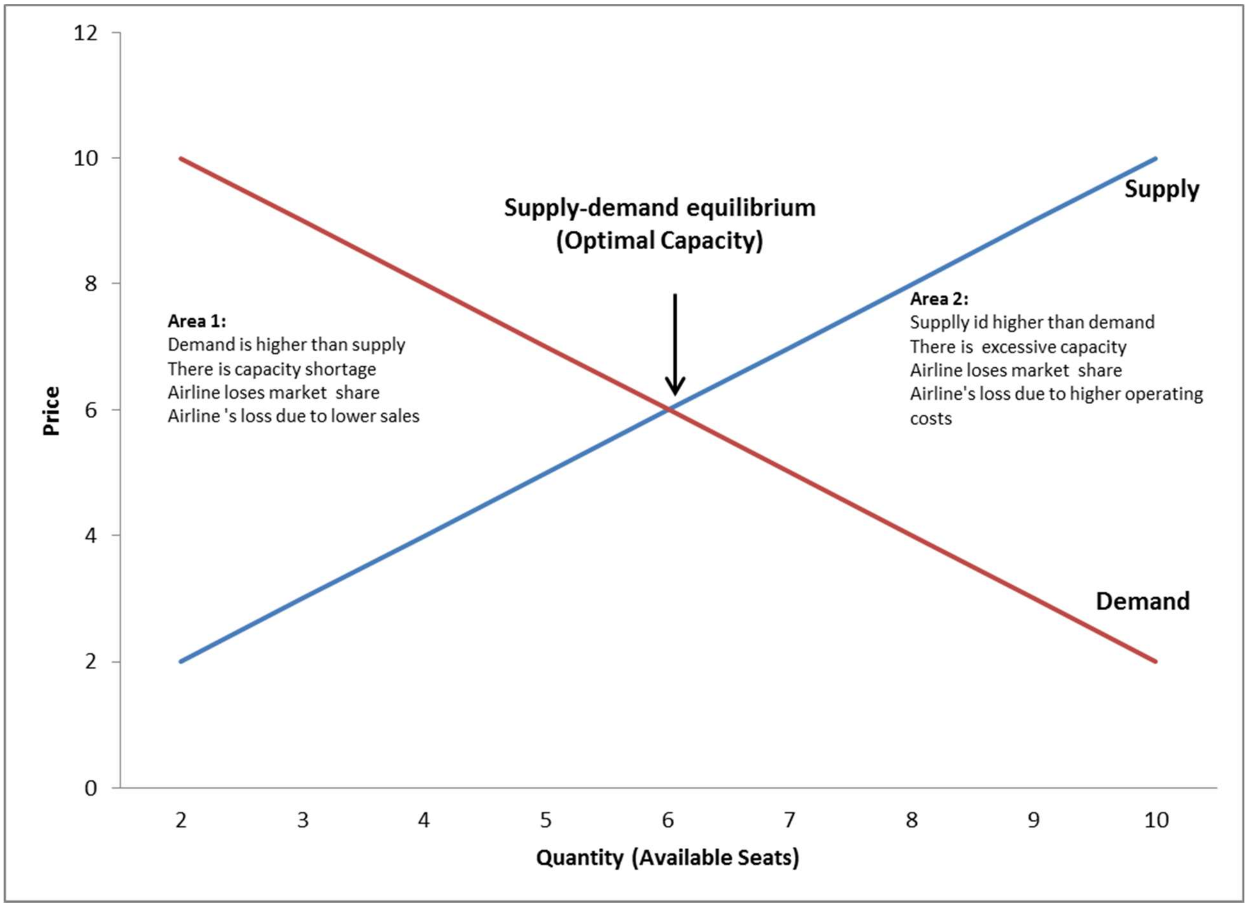

Figure 2.1 Supply-demand equilibrium flight markets

On the other hand, overestimating passenger demand leads an airline to offers their services in higher airfares (Figure 2.1, Area 2). In this scenario, airlines may increase its capacity to meet passenger demand. Higher airfares lead to less passenger demand, while higher capacity results in higher operating costs for the airline. As a result, this scenario results in airline's losses due to the lower willingness of customers to buy the ticket, because of higher airfares, as well as higher operating cost, because of excessive capacity. Finding the optimal quantity of supply-demand equilibrium, where an airline can provide the right available seats in right airfares to meet the potential passenger demand, may be challenging as many factors either in supply or demand side may cause an equilibrium shift. This disequilibrium may cause because of either a change of microeconomic, such as bad weather at airport, or of macroeconomic parameter, such as terrorist attacks of 9/11 in 2001. The impact of factor changes, which causes disequilibria, may be short or long term on the supply-demand equilibrium. However, disequilibria triggers a set of interrelated interactions among the equilibrium factors which in turn leads in equilibrium shift (Zou and Hansen, 2012).

Airline supply and demand analysis addresses investigating on passenger behavior, assessing an airline's response to the change of airfare or passenger income, and deriving the essential the demand-side information for supply-side decision makings (Vasigh et al., 2013). The study on the parameters on both sides of the supply-demand equilibrium has been a primary concern in the literature (e.g., Hsu and Wen, 2003; Wei and Hansen, 2005; Pitfield et al., 2010; Zou and Hansen, 2012). These studies attempted to identify the significant relations among the antecedents of potential travel demands and/or an airline's market share or benefit. Hsu and Wen (2003) addressed the supply-demand interaction between passenger demand and flight frequency through an integrated model to determine the optimum number of international flights for China Airlines. Pitfield et al. (2010) studied airline strategies to address the changes in flight demand and competition across the North Atlantic routes. Pitfield et al. applied a three-stage least-squares (3SLS) technique to simultaneously assess flight frequency, aircraft size and flight demand, and showed that flight demand inflation has a greater effect on flight frequency than aircraft size. In another study, Wei and Hansen (2005) used a nested logit model to reveal the factors of the quality of service in an airline's market share and total demand in non-stop duopoly markets. They found that, compared to aircraft size, an increase in flight frequency would lead to a higher return in market share. Zou and Hansen (2012) developed an econometric model to investigate the effect of aviation capacity on the supply-demand equilibrium in a competitive market. Their results indicated that a capacity change would trigger interactions among flight demand, airfares, flight frequency, aircraft size, and flight delays, ultimately resulting in an equilibrium shift. According to Zou and Hansen (2012), capacity constraint influences flight demand, reduces the number of flights, and inflates passenger expenses. In contrast, a greater capacity enables airlines to increase both the ticket price and flight frequency while reducing aircraft size. These studies clearly suggest that the modeling of air supply-demand equilibrium has been a crucial concern in the aviation literature. However, as noted by Gillen and Hazledine (2015), these studies primarily addressed the flight markets of the metropolitan cities in the U.S. or Europe, which are geographically and economically different from Australia. In those regions, the air transport systems are normally served by fully developed 360-degree hub-and-spoke networks[2] that do not exist in the Australian market. In addition, there are no secondary airports in the large cities in Australia to facilitate the activities of the low-cost carriers (Gillen and Hazledine, 2015). Table 2.1 provides a summary of some of the prior studies related to the key determinates of passenger demand forecasting and airlines capacity decisions. Table 2.2 also provides further information of the studies, listed in table 2.1, included the information of research category, applied methods, dataset specifications, and market under study.

As can be seen in Tables 2.1 and 2.2, the study on the supply-demand equilibrium of flight market has recorded a history of seven decades, started since the 1950's (Harvey, 1951). Some studies entirely focused on identifying the key determinants on the demand side and developing the passenger demand models (Harvey, 1951; Abed et al., 2001; Grosche et al., 2007). In these studies,

[2] This term was introduced by Gillen and Hazledine (2015) to explain the geographical difference of the flight market of U.S. and Europe and five regions including Australia. According to Gillen and Hazledine (2015), the geography of the U.S. and Europe is basically a two - dimensional grid which is different from that of some markets such as Australia which had long, thin, and linear entities.

passenger demand, as dependent variable, is econometrically modelled by a regression of the socio-econometric and demographic factors. From the supply side, Wei and Hansen (2007) applied the game-theoretic models on exclusively the supply side's factors to develop a capacity planning model. Many studies applied the factors on the both sides of supply-demand equilibrium to develop either a passenger demand model (e.g., Abrahams, 1983; Hensher, 2002; Fageda, 2005; Zou and Hansen, 2012; Zhang, 2015; Srisaeng et al., 2015) or a capacity planning model (e.g., Dresner, 2002; Hsu and Wei, 2003; Pai, 2010, Gillen and Hazledine, 2015), or even simultaneously the both (Jorge-Calderh, 1997; Ito and Lee, 2005; Pitfield et al., 2010; Brueckner and Zhang, 2010; Wang et al., 2014; Binova, 2015).

From the Tables 2.1, the prior studies applied a single or multiple dependent variable(s) for modeling. Number of passengers, as the primary variable, or RPM have been applied as the dependent variable in the demand modeling (e.g., Abed et al, 2001; Ito and Lee, 2005). From the supply side, flight frequency, aircraft size, total available seats have separately or simultaneously been applied as dependent variables of capacity planning (e.g., Jorge-Calderh, 1997; Dresner, 2002; Gillen and Hazledine, 2015). These variables were also used as explanatory variables of the demand modeling (e.g., Abrahams, 1983; Wei and Hansen, 2005; Wei and Hansen, 2005). Load Factor was only applied as the explanatory variable in the demand modeling (e.g., Suryani et al., 2010), however, flight delay was applied either as dependent variable (e.g., Brueckner and Zhang, 2010; Zou and Hansen, 2012) or as an explanatory variable in the modelling of passenger demand or capacity plan (e.g., Abrahams, 1983; Pai, 2010; Britto et al., 2012). Likewise, the prior studies primary applied airfare as an explanatory variable in passenger demand modelling (e.g., Abrahams, 1983; Hensher, 2002; Suryani et al., 2010) Airfare was also applied as a dependent variable in modelling (e.g., Ito and Lee, 2005; Britto et al., 2012; Gillen and Hazledine, 2015).

From Table 2.2, the prior studies applied mostly econometric techniques (e.g., Jorge-Calderh, 1997; Battersby and Oczkowski, 2001; Britto et al., 2012) or heuristic methods (e.g., Suryani et al., 2010; Zhang, 2015) in the demand forecasting. The studies mainly applied mathematical techniques for modelling of capacity planning to find the optimal solutions (e.g., Hsu and Wei, 2003; Wei and Hansen, 2005; Zou and Hansen, 2012). The studies largely applied the historical monthly data for modelling, mainly belonged to the domestic flight markets of USA, EU and Australia.

Table 2.1 Parameters under study- Literature Review

Author	Supply Side													Demand Side																
							Airline Factors									Socio-Economic Factors														
	Total Seats	Flight Frequency	Aircraft Size	Load Factor	Flight Delay	Service (Qualitative)	airfare	Jet-fuel expense	airline policy (full-service vs. Low-cost)	Competition	Hubbing Activity	Environmental cost	No. of spokes	Passenger	RPM	GDP per Capita	Unemployment	Import of Goods and Service	interest Rate	income	Labour Force	Total Governmental Expenditure	Consumer Price Index	Tourist	Buying power index	Interest Rate	Trunk	Population	Travel Duration	Distance
Harvey (1951)														D						E								E		E
Abrahams (1983)	E	E			E		E							D						E								E		
Jorge-Calderh (1997)		D	D								E			D						E				E				E		E
Abed et al (2001)														D		E		E	E	E		E								
Battersby and Oczkowski (2001) *							E								D					E										
Hensher (2002)						E	E			E	E			D		E														
Dresner (2002)	D									E																		E		E
Hsu and Wei (2003)		D					E					E		E															E	
Ito and Lee (2005)							D	E	E						D		E				E									
Fageda (2005)							E				E			D		E				E				E				E		E
Wei and Hansen (2005)	E	E	E				E							D						E										
Wei and Hensen (2006)		E	E				E						E	D						E										E
Grosche et al. (2007)														D		E									E				E	E
Wei and Hansen (2007) **	E	D	D					E																						
Pitfield et al. (2010)		D	D							E				D																E
Brueckner and Zhang (2010)		D	D		D			E				E			D															
Pai (2010)		D	D		E				E				E	E						E								E		E
Suryani et al. (2010)		E		E			E							D		E												E	E	
Zou and Hansen (2012)		D	E		D		E							D																E
Britto et al. (2012)					E		D		E	E				D						E				E				E		E
Chi and Baek (2013)		E												D						E										
Wang et al. (2014)		D	E					E		E				D		E											E	E		E
Zou and Hansen (2014)					E			E	E	E				E	D															E
Gillen and Hazledine (2015)	D		E				D		E	E														E			E	E	E	E

Author	Supply Side													Demand Side																
							Airline Factors									Socio-Economic Factors														
	Total Seats	Flight Frequency	Aircraft Size	Load Factor	Flight Delay	Service (Qualitative)	airfare	Jet-fuel expense	airline policy (full-service vs. Low-cost	Competition	Hubbing Activity	Environmental cost	No. of spokes	Passenger	RPM	GDP per Capita	Unemployment	Import of Goods and Service	interest Rate	income	Labour Force	Total Governmental Expenditure	Consumer Price Index	Tourist	Buying power index	Interest Rate	Trunk	Population	Travel Duration	Distance
Zhang (2015)								E	E					D		E								E				E		E
Srisaeng et al. (2015)							E	E	E					D		E								E		E		E		
Binova (2015)		D												D			E			E								E		E

* Other explanatory variables: Industry Production, Season

** Other explanatory variables: average aircraft operating cost per flight, average stage length for aircraft type, unit pilot cost per block hour, airline-specific factor

D: Dependent Variables, E: Explanatory Variables

Table 2.2 Market under study- Literature Review

Author	Modelling Method	Category	Data Type	Time Series	Market		Case Study
					International	Domestic	
Harvey (1951)	Regression model	Demand forecasting	Monthly	1948	×		USA
Abraham (1983)	Regression model	Demand forecasting	Quarterly	1973-1977	×		USA
Jorge-Calderh (1997)	Two stage least square method	Demand /Capacity forecasting	Monthly	1989-1996	×		EU
Abed et al. (2001)	stepwise regression technique	Demand forecasting	Yearly	1971-1992	×		Saudi Arabia
Battersby and Oczkowski (2001)**	Regression model	Demand forecasting	Quarterly	1992-1998		×	Australia
Hensher (2002)	Logit-regression model	Demand forecasting	Monthly	1997-98		×	Australia
Dresner (2002)	Reduced form estimating procedure	Capacity planning	Monthly	1995-1999		×	USA
Hsu and Wei (2003)	Optimisation model	Capacity planning	Monthly	1995-2001			Taiwan
Ito and Lee (2005)	Reduced form estimation of natural logit	Demand forecasting	Monthly	1986-2003		×	USA
Fageda (2005)	GRAVITY MODEL	Demand forecasting	Monthly	2001-2007		×	Spain
Wei and Hansen (2005)	Nested logit model	Capacity planning	Monthly	1995			USA
Wei and Hensen (2006)	Log-linear demand model	Demand forecasting	Monthly	2000-2006		×	USA
Grosche et al. (2007)	GRAVITY MODEL	Demand forecasting	Monthly	2004	×		Germany
Wei and Hansen (2007)	Game-theoretic models	Capacity planning	Quarterly	1987-1998		×	USA
Pitfield et al. (2010)	Three stage least square method	Demand/Capacity forecasting	Yearly	1990-2006	×		EU, USA
Brueckner and Zhang (2010)	Mathematical model based on a detailed theoretical model of competing duopoly airlines	Capacity planning	Yearly	1993-2008	×		World
Pai (2010)	Regression model	Capacity forecasting	Monthly	2000-2007		×	USA
Suryani et al. (2010)	System Dynamics	Demand forecasting	Yearly	1996-2007	×		Taiwan
Zou and Hansen (2012)	analytical model	Capacity planning	Monthly	2007-2012		×	USA
Britto et al. (2012)	Regression model	Demand forecasting	Quarterly	2003-2006		×	USA

Author	Modelling Method	Category	Data Type	Time Series	Market		Case Study
					International	Domestic	
Chi and Baek (2013)	Autoregressive distributed lag	Demand forecasting	Monthly	1996-2011		×	USA
Wang Et al. (2014)	Three-stage least square method	Demand/Capacity forecasting	Monthly			×	China
Zou and Hansen (2014)	Regression model	Capacity planning	Quarterly	2004-2008		×	USA
Gillen and Hazledine (2015)	GRAVITY MODEL	Demand forecasting	Monthly	2013-2015		×	Australia, Canada, New Zealand, Norway, Sweden
Zhang (2015)	Dynamic Panel Data Model	Demand forecasting	Monthly	2009-2013	×		Australia
Srisaeng et al. (2015)	Genetic Algorithm	Demand forecasting	Quarterly	1992-2014		×	Australia
Binova (2015)	Gravity model	Demand/Capacity forecasting	Monthly	2012	×		USA, Europe

2.5. Supply-demand equilibrium of the Australian domestic flight market

Despite the studies on supply-demand equilibrium in the aviation industry, the Australian flight market has garnered a small share of these research efforts (Gillen and Hazledine, 2015). The studies on this market largely focused on the demand modeling of the international flight market in Australia (Oppermann and Cooper, 1999; Hensher, 2002; Ashwini et al., 2012; Zhang and Findlay, 2014; Zhang, 2015).

Several studies have investigated the Australian domestic market in the last decade, focusing mostly on the estimation of air passenger demand for a regional airline hub or specific airport (Battersby and Oczkowski, 2001; Hensher, 2002) or passenger demand at a macro-level (Srisaeng et al., 2015). Battersby and Oczkowski (2001) developed an econometric analysis on the four major routes of Australian domestic market including the routes of Sydney- Melbourne, Sydney-Brisbane, Melbourne- Brisbane and Sydney- Coolangatta to identify the key drivers on passenger demand air travel behaviour. They developed demand models to identify the elasticity of some key determinants including airfare, industry production, and income on discount, full economy and business class passengers. Their findings highlight the passenger demand of Australian domestic market less elastic to the ticket price, and income, compared to those of the other markets across the globe. Hensher (2002) suggested an econometric model to estimate the passenger demand of Hazelton Airlines for the Canberra flight market and to study the feasibility of adding a hub at Canberra's international airport. Hensher (2002) defined some new parameters for route characteristics such as productions and attractions at the origins and destinations, and a definition of airline service quality based on attributes such as on-board services, aircraft type, and airline reputation. Srisaeng et al. (2015) proposed a forecasting model based using a genetic algorithm to predict passenger demand in the Australian domestic market. Srisaeng et al. used the aggregated monthly data of the socio-economic parameters such as population, GDP, GDP per capita, interest rates, airfares, and world jet fuel prices to predict passenger demand in the Australian domestic market at a macro level. That study also used dummy variables to address the effects of significant Australian incidents such as Ansett Australia's collapse in 2001, the Sydney Olympic Games in 2000, and the Melbourne Commonwealth Games in 2006.

On the supply side, Gillen and Hazledine (2015) merged the data of four Eastern/ Southern states in Australia with five other countries' data and used a gravity model to address the determinants of service and pricing, on the regional routes. Their study applied flight frequency and available seats to explain capacity, and in the absence of the air passenger factor, the dependent variable was directly addressed by the initial demographic factors, such as population and distance. They circumvented the bilateral relation between flight frequency and air passenger demand.

2.6. Optimal modeling of Capacity plans

Capacity planning can be very sophisticated particularly when it includes the entire route network compared to the individual routes (Teodorovic and Krcmar-Nozic, 1989). However, airlines need this planning as it is a prerequisite for the flight scheduling and crew allocation (Hsu and Wen, 2000). The determination of optimal flight frequency or type of aircrafts are among the main areas that prior studies have addressed besides the other topics such as hub-and-spoke network development, hub location, and airport capacity development (e.g., Teodorovic and Krcmar-Nozic, 1989; Jaillet et al., 1996; Hsu and Wen, 2000; Pitfield et al., 2010; Takebayashi, 2011). To determine the efficient flight frequency or aircraft size, studies have focused on meeting air traffic demand, maximizing airline profit, or improving the market share of competitive routes.

Some prior studies developed single- or multiple- objective mathematical models on a given network for an airline to find the optimum value either as flight frequency to maximise the airline's profitability or to minimise the operating costs (e.g., Teodorovic and Krcmar-Nozic, 1989; Jaillet et al., 1996; Hsu and Wen, 2000). These studies treated passenger demand as exogenous and ignored the interaction between flight demand and flight frequency (e.g., Hsu and Wen, 2003; Takebayashi, 2011; Mohammadian et al., 2019a). Further, these studies only applied flight frequency for capacity planning. As noted by Mohammadian et al. (2019a), the two variables of airline capacity decisions, flight frequency and aircraft size, need to be applied together to reflect a practical and comprehensive picture of airlines policies in capacity planning.

Some studies in the context of economic competition applied the supply-demand equilibrium in hub and spoke network design and the hubbing problem (Hansen and Kanafani, 1987; Hansen, 1990; Adler, 2001; Hsu and Wen, 2003; Takebayashi, 2011). Hansen and Kanafani (1987) developed a model to predict passenger demand resulting from different airlines' hubbing strategies. They indicated that the international traffic through an airport is highly sensitive to the airline's strategy. Hansen (1990) developed an airline hub competition model that integrated airlines and passengers route choices. He applied flight frequency on the origin-destinations routes of a hub-dominated network as the decision variable. Similar to Hansen and Kanafani (1987), he assumed passenger demand to be inelastic with respect to the airfare and airline service changes.

Adler (2001) proposed a demand model based on a two-stage Nash best-response game. The model maximises airline profit by developing an optimal hub-and-spoke network. In the model, flight frequency, aircraft size and airfares are the decision variables. Takebayashi (2011) proposed an extended bi-level market model of airline network design to maximise airline profit and applied aircraft size besides flight frequency as decision variables. These studies assume flight demand to be fixed or exogenous and apply profit maximization as the model objective. Hsu and Wen (2003) developed a model under supply-demand equilibrium to obtain the optimal number of international flights for China airlines on a hub and spoke network. The model includes two submodels, a passenger airline flight choice model to estimate an airline's market shares as well as predict market sizes for all routes under a network, and an airline flight frequency programming model to find the optimal flight frequency to maximise the airline's total profit. The submodels are later integrated to analyze the supply-demand interactions. From their model, capacity planning is more accurate as it considers the interaction between flight frequency and passenger demand.

Wei and Hansen (2007) applied three different game-theoretic models to empirically determine the strategic capacity plan in duopoly markets. Their model comprises two submodels; cost function and demand sub-model, targeted to choose the optimal flight frequency and aircraft size to maximise the airline's profit. The demand sub-model is based on a nested logit model which it assumes flight frequency and aircraft size as exogenous variables, and in turn ignores the interactions among passenger demand, flight frequency and aircraft size in the modeling. Their findings reveal the impact of flight distance on airlines' capacity planning. Furthermore, they highlight how a competitive environment may influence on airlines' strategies of capacity planning.

2.7. Economies of Density

Airlines must focus on their cost structure and find the solutions to achieve the higher levels of productivity. The aviation industry is highly capital intensive, therefore airlines profitability depends upon fuel efficiency, aircraft utilisation, and labor expenses. The theory of cost is one of the significant theories of economies which airlines must apply to develop their business strategies and frameworks. Cost management of airlines comprises the elements more than just minimising the labor expenses or jet fuel costs. It includes finding the right cost structure to optimise the expenses across the entire business (Vasigh et al., 2013, p. 200). When airlines come to decide about the theory of cost, which it would apply as a base for cost structure modeling, there are different cost theories comprising economies of scale, economies of scope, and economies of density.

Economies of scale refer to "*the advantages gained when long-run average costs decrease with an increase in the quantity being produced*" (Vasigh et al., 2013, p. 198). This theory is common in highly incentive industries with relatively high fixed costs such as railroads or aviation industry. Economies of scope refer to "*the situation where the company can reduce its unit costs by leveraging efficiencies through sharing of resources for multiple projects or production lines*" (Vasigh et al., 2013, p. 199). In a simple statement, it might be more cost efficient if multiple projects or processes when they are implemented together compared to the time they are performed separately. Economies of density refer to "*cost reductions that result when a company utilizes a bigger plant size in the production a single product*" (Vasigh et al., 2013, p. 27). Economies of density are achieved through the operations consolidation. The aviation industry may apply this theory by developing the hub-and-spoke networks. Under a hub-and-spoke network, airlines likely enable to increase passenger density and fly aircrafts with higher load factor as well as to fly more on their operating routes (Vasigh et al., 2013, p. 200). Airlines may apply one or a combination of these mentioned theories to model their cost controls. Low cost carriers vs. legacy airlines are a good example showing how pursuing different cost policies may differentiate between airlines operation.

Early studies on cost economies primary concentrated on proving the existence of economies of scale in the aviation industry. White (1979) identified a negligible impact of economies of scale at the overall firm level in the airline industry. This finding has been endorsed by the other studies (e.g. Caves et al.,1984; Gillen and Morrison, 2005). Liu and Lynk (1999) discussed the post-deregulation of the US aviation market and highlighted the existence of economies of scope. Bailey and Friedlaender (1982) proved the existence of economy of scope in the form of economies of networking. However, most recent studies on cost economies have been discussed the existence of economies of density. By having the access to the hub-and-spoke networks, airlines enable to apply relatively larger aircrafts to move passengers, compared to point-to-point flight on their daily operations, which in turn increase airlines available seats miles. Having access to the hub-and-spoke network, airlines also enable to add new spoke to their networks and increase the traffic density which in turn lower the marginal operating cost per passenger. This consequently improves airlines' competitiveness, and 'capabilities for further expansion (Brueckner and Spiller, 1994). As discussed by Baltagi et al. (1995), higher level of an airline's output in terms of more available seats or number of departed flights negatively influences the average operating costs. This confirms that higher traffic density would lead in lower unit costs that in turn result in lower operating costs per aircraft movement, which it proves the presence of economies of density (Zuiderg, 2014).

Economies of density describes the growth of a firm's output with respect to a constant network size and route structure, whereas economies of scale addresses changes in the network size. Regarding these terminologies, the authors studied the potential cost saving originated from the growth in either output or network. Most of the prior studies found the benefits of economies of density versus no impact of economies of scope in increasing the potential cost saving. In more details, there are cost benefits arising from the traffic growth or, in another word, higher density, given by having a constant network size. By contrast, there is no cost advantage for airlines to operate larger networks (Jara-Diaz et al., 2013).

As discussed by Zou and Hansen (2012), given by no congestion, economies of density lead airlines to provide more plane miles by either a greater number of flights or larger aircrafts. More plane miles result in less unit operating costs for airlines, and consequently lower generalised unit cost for passengers. Hence, without capacity constraints, there is an iterative loop creating higher economic density on the demand side, and more plane-miles on the supply side of the flight equilibrium.

However, this statement is no longer valid once congestion in terms of capacity constraints is added to the equilibrium. Capacity constraints introduce a new factor, named flight delay, to the equilibrium. As a result, more density results in higher flight delays due to capacity constraints. Flight delays incur extra cost for airlines, offsetting the economies of density. In fact, higher flight delays lead to less passenger demand either directly or indirectly as an outcome of the airline responses (Zou and Hansen, 2012).

2.8. Flight Delay

Delay is a measure applied to assess the performance of all transport systems (Wieland, 1997). It is also identified as a key driver affecting customer loyalty (Vlachos and Lin, 2014). With the increase in air transport demand and supply-side constraints, the subject of flight delays has drawn much research interest in the past two decades (Britto et al., 2012).

While some scholars studied the factors that initially cause flight delays (Abdel-Aty et al., 2007), others focused on how flight delays propagate in a flight network (AhmadBeygi et al., 2008; Wong et al., 2012). Some studies treated flight delays as an explanatory variable in flight demand modeling (Hansen, 2002; Britto et al., 2012) or capacity planning (Zou and Hansen, 2014). Others studied the financial and customer-related aspects of flight delays (Ferrer et al., 2012; Lubbe and Victor, 2012; Peterson et al., 2013).

In some studies, flight delays were used to index an airline's performance and assess airport efficiency (AhmadBeygi et al., 2008; Pathomsiri et al., 2008). These studies identified the parameters of flight delays, including seasonal and temporal factors (Abdel-Aty et al., 2007), weather and climate (Abdelghanya et al., 2004), airport specification and demand patterns (Dillingham, 2005), capacity constraints (Wong et al., 2002), aircraft type and number of scheduled flights (Kafle and Zou, 2016), and airline and airport operational performance (Reynolds-Feighan and Button, 1999; Muelle and Chatterji, 2002). For instance, Abdel-Aty et al. (2007) found evidence of regularity in the arrival delays of non-stop flights at Orlando's International Airport in the U.S. They identified the time of the day, day of the week, season, flight distance, and time buffer between scheduled flights as the determinants of flight arrival delays. According to Abdelghanya et al. (2004), bad weather accounts for 75% of all flight delays which can snowball over time due to the interdependencies between airline resources (aircraft, flight and cabin crew) and airport facilities (landing bridges and apron crew).

Similarly, Abdelghany et al. (2004) highlighted airline recovery action as a factor to curb the impact of adverse weather on the scheduled flights. Seasonality and daily propagation patterns are identified as antecedents of delays when estimating the distribution of flight delays (Tu et al., 2008). Tu et al. (2008) attributed the change in flight demand and weather due to seasonality and crew connection issues and use the delay built-up from earlier flights to explain the daily propagation pattern of flight delays.

Airlines desire a high level of airport utilization and seek to minimise their operating costs (AhmadBeygi et al., 2008). Therefore, with realistic airspace constraints, a disruption in the scheduled flights may affect subsequent flights, which may lead to passenger dissatisfaction. According to Wong et al. (2002), capacity constraints increase the runway congestion level, which is also a major cause of operational flight delays.

Prior studies have found flight delays to influence demand modeling or capacity planning. Pai (2010) reported flight delays as an important factor that affects the flight frequency and aircraft size on airline routes in the U.S. According to Pai (2010), more flight delays may lead airlines to reduce the frequency of flights and use smaller aircrafts. Britto et al. (2012) reported that flight delays result in lower flight demand and higher airfares on a route, creating a decline in both passenger and airline welfare. Zou and Hansen (2012) discussed how airlines attempt to reduce flight delays by shifting to fewer flights and using larger aircraft. Zou and Hansen (2014) noted that flight delays increase airfares because airlines tend to pass on the delay cost to the travelers. Appendix 2.1 provides a summary of some of the prior studies in the field of flight delay forecasting and modeling.

2.9. Summary

With respect to the review on the prior studies which provided on the previous sections of literature review chapter, this section provides a summary of research problems. These problems/ gaps are applied to design the study framework.

2.9.1. Determinants of air supply-demand equilibriums

As discussed in Section 2.2-5, a number of studies have investigated the regional, national or international data to identify the factors in either stimulating the flight demand (Chi and Baek, 2013; Fridstorom and Thune-Larsen, 1989; Ito and Lee, 2005; Jorge-Calderón, 1997; George et al., 1974; Wei and Hansen, 2006), or determining the optimum capacity on high demand routes or hub-and-spoke networks (Givoni and Rietveld, 2010; Hsu and Wen, 2003; Pitfield et al., 2010; Teodorovic and Krcmar-Nozic, 1989; Zou and Hansen, 2012).

None of the existing studies explored the determinants that drive the supply-demand equilibrium on the level of the origin-destination routes and the parameters that influence the capacity decisions of the dominant carriers in the Australian domestic market. In fact, previous research omitted how the domestic airlines managed and met the demands of the potential passengers of the regional routes and translated this demand into capacity algorithms. Airline strategies for capacity decisions appear to depend not only on flight demand but also on other parameters such as the characteristics of the endpoints, competition from other airlines and/or other transport substitutions, and airline-related factors such as jet fuel cost and airline policy.

As discussed in Section 2.4, no study has comprehensively addressed the subject of airline capacity decisions in the Australian domestic market. Similar studies in the literature primarily focused on domestic or international flight routes to large cities in the U.S. or Europe whose geography of the flight routes and the economics of passenger aviation are vastly different from the Australian domestic flight market (Gillen and Hazledine, 2015).

Therefore, one of the key purposes of this study is thus to investigate the supply-demand equilibrium of domestic air transport in Australia to reveal how the domestic airlines developed their capacity algorithms considering the number of flights, aircraft size, and load factor. The research questions in this section are thus stated as follows: These questions are targeted to address in Chapter 3 of this study.

1. Do airline capacity strategies for the Australian market differ, based on the short, medium and long-haul routes? If so, what factors drive these strategies?
2. How do the supply side parameters, including competition, participation of low-cost carriers, and jet fuel cost inflation, affect passenger demand?
3. How do the demand-related factors influence the airlines' capacity decisions?

2.9.2. Determinants of flight delay

As discussed in Section 2.6, flight delay is known as one of the key drivers in the supply-demand equilibrium. Despite the significance of flight delays on the performance of the Australian domestic aviation industry, empirical studies have yet to examine the factors affecting this phenomenon in Australia. Studies have addressed the U.S. or European markets which are geographically and economically different from the Australian domestic flight market. As discussed by Gillen and Hazledine (2015), the air transport system in the U.S. and Europe is supported by mature 360° hub-and-spoke networks. In addition, secondary airports are used in the larger cities to facilitate the activities of the low-cost carriers. Such facilities do not exist in Australia (Gillen and Hazledine, 2015). Using the data from the Australian domestic aviation market, one of the purposes of this study is to address this gap. Further, most studies employed a micro level analysis involving daily data to investigate the factors that influence flight delays (Hansen, 2002; Abdel-Aty et al., 2007; AhmadBeygi et al., 2008; Ding and Li, 2012). In contrast, this study addresses this issue by including new route- and Australian domestic-level factors such as jet fuel price, participation rate of the low-cost carriers, and airline competition to model flight delays. These research problems are aimed to address in Chapter 4 of this study.

2.9.3. Optimal Capacity Planning

Airlines need to consider the economies of density in the air supply-demand equilibrium for any model in demand modeling or capacity planning. This theory builds logic behind the interactions among passenger demand, flight frequency, aircraft size, airfare, and flight delay. Therefore, the economies of density thinking, this study proposes an optimisation model for airline capacity planning of individual routes of a hub and spoke network or an airport. The following are the key problems/gaps which this study aims to address in Chapter 5:

- Different from prior studies which majority applied pure theoretical approaches to develop the optimisation model, this study aims to develop an optimisation model based on a passenger demand function derived from the empirical analysis on parameters which practically applied by airlines for capacity planning.
- The prior studies have applied an airline's profitability or operating cost as the model objective to determine the optimal number of flights under supply-demand equilibrium. This study's novelty considers flight demand as the objective, and flight frequency and aircraft size as the decision variables.
- This study includes all the key drivers of supply-demand equilibrium and their relations in modeling to empirically estimate the passenger demand equation as the model objective. In a new optimisation framework, this equation is applied to identify the optimal flight frequency and aircraft size.
- Compared to the prior studies of capacity planning, most of which used aggregate micro-level data, this study applies macro-level factors in modeling.
- This study highlights how passenger demand elasticity to the variables of capacity planning differs among the routes, as a result of different markets specifications.

Chapter 3

Identification of key drivers on airlines' capacity decisions

3.1.Introduction

This chapter is to develop an econometric model to identify the key drivers of airlines capacity planning under supply-demand equilibrium of flight market. This chapter begins with a background of airline capacity planning. Then it is followed by a description of Australian domestic market where is applied as the research case study. Section 3.4 identifies the model parameters, followed by Data Description. It then discusses the econometric technique to analyse the data, followed by model formulation in Section 3.6. Section 3.7 provides pool results of the econometrical analysis. The final section concludes the findings of the chapter.

3.2.Background

Airlines always seek to hold their core competencies to adequate standards through competitive service quality and airfares to control their market share and improve the level of profitability. For this purpose, capacity planning is one of the primary tools that carriers rely on to manage and control air traffic demand and airfares (Wei and Hansen, 2005; Carey, 2015). As such, the carriers may alter the number of flights, use different types of airplanes, upgrade the seats in the aircraft, and even increase the load factor to maintain their market share and profitability, which can occasionally lead to passenger dissatisfaction (Stock, 2013). Indeed, capacity decisions combined with the traditional approaches such as the control of airfares and hedging contracts have historically been used by airlines to mitigate the risk of bankruptcy arising from unexpected events such as the 9/11 attacks, the 2008 global financial crisis, and the oil price surge in 2008 (Wei and Hansen, 2005; Purnanandam, 2008). However, the increase in airfare appears to have been ineffective for airlines post deregulation because of the keen competition, which is expected to grow as the low-cost carriers continue lift their market share (Borenstein, 2011).

Airlines have used hedging contracts to reduce any financial loss stemming from the fuel price volatility. However, such financial instruments have not been completely successful because of the complexity of the hedge fund strategies and the high cost of hedging (Brailsford et al., 2001; Carter et al., 2004). Thus, airlines employ various financial strategies, from not hedging to fully hedging using a combination of products (SEC, 2005-2015). Thus, the role of capacity decisions in airline profitability is expected to become more important because of the diminishing relative effect of the other airline tools such as airfare increases or hedging contracts.

According to the discussion in section 2.8.1 of literature review section, the key research question is to identify the underlying factors in capacity decisions, as best practices, in the supply-demand equilibrium. Identifying these factors provide an effective base for the forecast of air transport activities in the Australian domestic air market. Having reliable forecasts in the aviation industry are key information for airlines, investors, and the other stakeholders, and enhance decision making at various levels, such as fleet planning, airline route network development, and civil aviation and airport development (Srisaeng et al., 2015). In fact, possessing accurate knowledge enables the stakeholders to identify the best algorithm on capacity regarding the changes in travel demand and how these capacity decisions influence airline demand, market share, and profitability (Wei and Hansen, 2005).

Any capacity decision in the aviation industry triggers an interaction between the factors of supply and demand that ultimately leads to an equilibrium shift. Capacity decisions affect the interrelated interactions among the passenger flow, flight frequency, aircraft size, and load factor that would result in changes in airfare and overall capacity, or even flight delays or cancellations (Zou and Hansen, 2012).

3.3.Case Study Context: Australian domestic market

The Australian aviation industry was founded to connect Australia's regional communities to the major cities in Australia (Baker and Donnet, 2012). The industry, historically controlled by the Federal Government, was de-regulated in 1989. Since then, there has been several controversial changes in the domestic aviation industry (BTE, 1995). From the passenger's perspective, de-regulation was successful, resulting in lower average airfares and more flights, and improved the service quality due to the keener competition between the legacy and low-cost carriers (BTE, 1995). The domestic aviation market is expected to expand because of the population growth and the vast distances between the cities of Australia (Srisaeng et al., 2015). According to the annual reports of the Department of Infrastructure and Regional Development (BITRE, 2006-2016), 58.4 million passengers were carried on domestic flights for the year ending in June 2016 across 72 routes in Australia, an increase of 2.1% y-o-y[3] and 32.1% from June 2006. From the carriers' perspective, the effect of de-regulation was not as clear cut. Despite the improvement in production efficiency with the inclusion of the low-cost carriers as the new service providers, airline profitability was adversely influenced by price competition and higher levels of overall capacity, particularly during the global recession periods such as the downturn from 2007-2009 (BTE, 1995). Consequently, the Australian aviation industry experienced several consolidations, bankruptcies, takeovers, and loss of airports (Baker and Donnet, 2012). Two low-cost carriers, Jetstar and Tiger Airways, with about 35% of the market share in 2015, and two legacy airlines, Qantas and Virgin Australia, were recognised as the incumbent suppliers in the domestic air market. (Srisaeng et al., 2015).

[3] Year On Year

3.4. Parameters

Table 3.1 describes the model parameters. Three variables, flight frequency (**FF**), aircraft size (**ASIZE**), and load factor (**LF**), are selected to reflect the decisions that airlines make to manage their capacity regarding the specifications of flight demand. These variables are collectively known as the quality of service (Jorge-Calderón, 1997). In the absence of historical data on the airlines' usage of aircraft types in the Australian domestic market, the average aircraft size is applied in this study like the previous studies (e.g. Jorge-Calderón,1997; Pitfield et al., 2010). This chapter also analyzes the variable of available seats, which reflects an airline's capacity to carry passengers. This variable is used to investigate how demand or airline-related factors may influence the total capacity provided by the airlines with respect to the different capacity algorithms. The available seats are influenced by the parameters on both sides of the supply-demand equilibrium of the flight market (Jorge-Calderón, 1997; Barrett, 2004; Pitfield, et al., 2010). Air passenger (**PASS)** is the most well-known and frequently used parameter used to reflect the air traffic demand. A stronger flight demand causes an increase in flight frequency, aircraft size, and load factor (Fridstorom and Thune-Laresen, 1989; Jorge-Calderón, 1997; Ito and Lee, 2005; Chi and Baek, 2013).

Table 3.1 Description of Parameters

Name*	Definition	Type	Data source
Flight Frequency	Total number of flights for a given route per month.	Monthly/OD	DIRD, Domestic Aviation Activity Reports (http://bitre.gov.au/)
Average Aircraft Size	Average aircraft size calculated as Number of Available Seats divided by Flight Frequency for a given route and time period	Monthly/OD	DIRD, Domestic Aviation Activity Reports (http://bitre.gov.au/)
Load Factor (%)	Average Passenger Load Factor for a given route per month	Monthly/OD	DIRD, Domestic Aviation Activity Reports (http://bitre.gov.au/)
Number of Available Seats	Total number of available seats for a given route per month	Monthly/OD	DIRD, Domestic Aviation Activity Reports (http://bitre.gov.au/)

Name*	Definition	Type	Data source
Number of Passengers	Total number of passengers for a given route per month	Monthly/OD	DIRD, Domestic Aviation Activity Reports (http://bitre.gov.au/)
Jet Fuel Price	Average monthly fuel price in US airline industry (U.S. Gulf Coast Kerosene- Type Jet Fuel spot price FOB)	Monthly/World	U.S. Energy Information Administration (https://www.eia.gov/)
Number of Low-Cost Carriers	Number of low-cost carriers participating for a given route and time period	Monthly/OD	DIRD, Domestic Aviation Activity Reports
HHI	Hirschman-Herfindahl Index on the route per month	Monthly/OD	DIRD, Domestic On-time Performance Reports (http://bitre.gov.au/)
Employment Rate	Calculated as the product of Employment Rate (%) of each city pair for a given route and time period (in this study)	Monthly/State[4]	Department of Employment (http://lmip.gov.au/)
Airfare	Australian Domestic Airfare - Real Best Discount (ref. month: July 2003) for the given period	Monthly/ Australia Domestic Market	DIRD, Domestic Air Fare Indexes (http://bitre.gov.au/)
Population (in billion)	Calculated as the product of Population of each city pair for a given route and time period (in this study)	Monthly/State	ABS (http://www.abs.gov.au/)

*Information covers both directions of each city pair for a given route.

Airfare (**FARE**) is a significant explanatory variable of air travel. All other parameters being equal, a higher airfare leads to lower levels of flight demand. Due to the unavailability of the average monthly airfares of the routes under study, the economy-class airfare index in the Australian domestic market was used as a proxy for this parameter. The socio-economic factors have been recognised as the primary parameters in the supply-demand equilibrium that are normally used for demand modeling (Ito and Lee, 2005). These factors reflect the commercial, cultural, and industrial activities in a flight's origin and destination. Higher levels of the social-economic factors positively stimulate flight demand (Ito and Lee, 2005). This study applies the product of population

[4] From a report published by the Department of Employment, the three- month moving average of the original quarterly data is used to provide the monthly data on the employment rate.

(**POP**), and employment rate (**EMP**) of the origin-destination (OD) pairs as proxies for the socio-economic factors.

Jet fuel cost (**JFuel)** is the most volatile airline operational expense that affects the capacity algorithms of the airlines. Various scholars have addressed this parameter as a key factor that adversely influences the quality of flight service (e.g., Borenstein, 2011; Borenstein and Rose, 2014) and passenger satisfaction in terms of flight cancellations and delays that ultimately results in a reduction in flight demand (Stock, 2013). The findings of Ito and Lee (2005) surprisingly did not recognise jet fuel cost as a significant parameter in demand modeling. Borenstein (2011), and Borenstein and Rose (2014) addressed the fluctuation of jet fuel cost as a factor in the revenue volatility of the airline, not for changing an airline's capacity algorithms. Due to the unavailability of the jet fuel cost information in the Australian domestic market, this study uses the monthly information of the U.S. Gulf Coast Kerosene-Type Jet Fuel Spot Price to address this parameter in the proposed model. Jet fuel have been priced globally, correlated to diesel and gasoline prices and related to the passenger demand fueled by global economic growth (Davos, 2018). Therefore, a high-level correlation is expected between the monthly jet fuel prices of the Australian domestic market with those of the U.S. Gulf Coast Kerosene-Type Jet Fuel Spot Price. Consequently, the proposed proxy may sufficiently address the jet fuel price of Australian domestic market in this study.

Compared to the legacy airlines, the low-cost carriers have followed different patterns in demand modeling and capacity algorithms. The presence of the low-cost carriers in the flight market has been hypothesized to positively affect flight demand and quality of service (Barrett, 2004; Pels, 2009). This study addresses this parameter by the number of participating low-cost carriers for the given route and period.

Competition between the airlines reflects a significant effect on flight demand in air transportation (Barrett, 2004; Pitfield et al., 2010; Gillen and Hazledine, 2015). Gillen and Hazledine (2015) have posited that stiffer competition results in lower ticket prices and flight service improvement, both of which stimulate flight demand. However, the Australian aviation industry has experienced many consolidations, bankruptcies, takeovers or loss of airports because of market competition policies since de-regulation (Baker and Donnet, 2012). The Hirschman–Herfindahl Index (**HHI**) was initially selected for this study as an indicator of airline competition in the routes examined. The HHI is a standard approach used to measure the airlines' competition levels for a specific route (Barrett, 2004; Pitfield et al., 2010; Gillen and Hazledine, 2015). The HHI is calculated for route i in period t as given below:

$$\mathrm{HHI}_{\mathrm{it}} = \mathrm{MS}_{1\mathrm{it}}^2 + \mathrm{MS}_{2\mathrm{it}}^2 + \mathrm{MS}_{3\mathrm{it}}^2 + \ldots + \mathrm{MS}_{\mathrm{nit}}^2$$

where MS_{nit} is the market share of airline n on route i in period t. The HHI holds values from "1" to "0" reflecting monopoly and perfect competition, respectively, in the market, and the HHI includes the participation of all the active airlines. As the data are cross-sectional and include the information of 21 OD pairs, 21 dummy variables were included in the model. Considering these dummies over the time period, the information was recognised as panel data, and a time-series analysis was conducted for all the routes simultaneously.

To obtain adequate datasets, this study relies on several public and private agencies, including the Australian Bureau of Statistics (ABS) and the Department of Infrastructure and Regional Development (DIRD). Proxies were used for some parameters in the case of the non-availability of monthly state data including the jet fuel costs and the average monthly ticket prices of the OD markets. The information regarding the parameters of the targeted routes was estimated from the information on the origins and destinations. The data were seasonally adjusted to reflect the industry's demand pattern.

3.5. Data

The available data cover twenty-one major flight routes among the state capitals of Adelaide, Melbourne, Sydney, Perth, Darwin, Hobart, Canberra, and Brisbane. Figure 3.1 presents the routes that were targeted in this research and comprises the bilateral monthly data between origin and destination from January 2004 to December 2015. This market was chosen due to the availability of historical data of the different demand- and airline-related variables used in this research. This market was a good and reliable sample of the Australian domestic market providing the possibility of an effective analysis on the factors of competition and the participation of the low-cost carriers.

The dataset contains the data of four dominant airlines: Qantas, Virgin, Jetstar, Tigerair, and the other carriers that participated during this period include QantasLink, Regional Express, Virgin Australia - ATR/F100 Operations, and Virgin Australia Regional Airlines. The selected market provides enough time-series information of a maximum of 138 observations for each route. However, some routes, including Brisbane-Hobart, Darwin-Perth, and Darwin-Sydney, did not operate for all twelve months; hence, the dataset was sparse for these routes.

Figure 3.1 Targeted Domestic Origin-Destination Flight Routes

(for reference only; identical to Figure 1.4)

Distance is the most common locational factor (Russon and Riley, 1993). This factor affects demand in two diametric ways. First, a longer distance negatively affects flight demand because of the reduced social and commercial interaction between the origin and the destination. Conversely, the relative significance of air travel increases at greater distances compared to the other modes of transportation (Jorge-Calderón, 1997). Domestic low-cost carriers such as Jetstar participate less than the full-service airlines such as Qantas on the long-haul routes because of their limited access to the hub-and-spoke networks (Whyte and Lohmann, 2015).

3.6.Methodological Framework

3.6.1. Model Specification

As discussed below, three key specifications need to take into accounts to develop the methodological framework, and identify the model, as the best practice, to analyse the data. These three specifications are as below.

- the data is categorized as panel data (Cross-Sectional time-series)

- Distance needs to be account is the analysis
- There is endogeneity effect between flight demand, and the variables of capacity decisions

3.6.1.1. Panel Data Analysis

Past studies recognised the gravity and econometric models as being the more popular techniques to forecast **PASS** and flight services (Fildes et al., 2011; Gillen and Hazledine, 2015). The same studies noted that while the gravity models inherently fit the demand modeling of air traffic, their performance was ineffective in modeling markets with capacity constraints or estimating the effects of distance on market size (Gillen and Hazledine, 2015). Thus, this method appears to be ineffective for the framework of the supply-demand equilibrium intended in this study.

As the dataset is categorized as a cross-sectional time-series, two methods of panel data analysis, fixed effects and random effects general least squares techniques are applied to estimate the regression models (Maddala and Lahiri, 1992). The fixed effects model assumes that the panel specific effects are correlated with the independent variables. The random effect model assumes that the panel specific effects are uncorrelated to the other covariates of the model. If the random effects assumption is valid, the random effects model can provide more effective outputs than the fixed effect model, otherwise the random effects model is inconsistent (Wooldridge, 2013). The more effective model can be selected by applying a Hausman test with the following null hypothesis: H_o - the difference between the coefficients of two models of fixed and random-effects, is not systematic. If H_o is not rejected, then the coefficients estimated by the random effects model are more effective than those of fixed effects model (Wooldridge, 2013).

Appendix 3.1 presents the coefficients of the fixed effects and random effects models which provide the outputs of the Hausman test for the passenger model. The test output of demand model rejects H$_o$ ($x^2 = 159.48$). Therefore, the outputs of fixed effects model are more effective than those of the random-effects model. However, as the distance-related factors including distance or time travel ratio[5] are time-invariant, the fixed effects model is not applicable as these variables are omitted in the modeling due to the correlation with the routes dummy variables (Wooldridge, 2010, p.288).

3.6.1.2.Distance-related factor analysis

To assess the distance related factor in modeling, the market under study is categorized into three distance groups of short-, medium- and long-hauls as proposed by Abrahams (1983). Table 3.2 presents the routes in the distance grouping. Regarding the distance grouping, Appendices 3.2, 3.3, and 3.4 provide the descriptive statistics of the parameters for three distance groups. Table 3.2 also provides a definition of the each of the groups by distance.

Table 3.2 Flight Route Categories Based on Distance

Group	Distance	Flight Route
Short-haul	Less than 800 km (≈ 500 miles)	Adelaide - Melbourne, Brisbane - Sydney, Canberra - Sydney, Canberra - Melbourne, Hobart - Melbourne, Melbourne - Sydney
Medium-haul	Greater than 800 km (≈ 500 miles) & less than 2400 km (1500 miles)	Adelaide - Brisbane, Adelaide - Canberra, Adelaide - Sydney, Adelaide - Perth, Brisbane - Canberra, Brisbane - Hobart, Brisbane - Melbourne, Hobart - Sydney
Long-haul	Greater than 2400 km (≈ 1500 miles)	Brisbane - Darwin, Brisbane - Perth, Darwin - Melbourne, Darwin - Perth, Darwin - Sydney, Melbourne - Perth, Perth - Sydney

[5] The time travel ratio is calculated as the travel duration by car divided by travel duration by flight for a given route.

3.6.1.3.Endogeneity effect

In such a complex system of capacity planning, changing a factor on each side of the equilibrium triggers interrelated interactions among the parameters that would cause an imbalance condition, subsequently leading to an equilibrium shift. For example, a bilateral condition, which is known as endogeneity, has historically been discussed between **PASS** and the parameters of capacity decisions in the literature (Jorge-Calderón, 1997; Pitfield et al., 2010). The endogeneity problem normally occurs when an explanatory variable is correlated with the error term. One common cause of endogeneity is a loop of causality between the independent and dependent variables of a model (Wooldridge, 2013). No doubt, higher demand results in greater capacity from the airlines in terms of more **FF** and a larger **ASIZE**. Further, greater capacity improves the quality of flight service and lower **FARE,** which stimulate flight demand (**PASS**). According to Pitfield et al. (2010), relying on the ordinary regression (OLS) techniques in econometrics can potentially result in a biased and inconsistent estimation. Therefore, to counter the possibility of endogeneity between passengers and the four dependent variables **FF**, **ASIZE**, **LF**, and **SEATS**, this study avoids using such techniques for modeling.

To verify the endogeneity between **PASS** and the model's dependent variables, the Durbin-Wu-Hausman (DWH) test is applied as suggested by Davidson and MacKinnon (1993) on the four dependent variables. This test is developed by considering the residuals of the endogenous variable as a function of all exogenous parameters in a regression of the original model. The DWH test examines the null hypothesis that endogeneity between the parameters (e.g., **PASS**) and the dependent variable (e.g., **FF**) has no significant effect on the estimates.

Table 3.3 shows the outputs of the endogeneity test. In general, a small p-value ($p < .05$) indicates the rejection of the null hypothesis. The OLS method is therefore not consistent. The results of the

DWH test confirmed the indicated hypothesis regarding the endogeneity between the dependent variables and **PASS**. Therefore, the application of ordinary linear regression model (OLS) can potentially result in a biased and inconsistent estimation.

Table 3.3 Durbin-Wu-Hausman Test Outputs

Test of endogeneity	
H0: variable is exogenous	
FF& PASS:	
Durbin (Score) $\chi^2(1)$	= 9.69 (p-value= 0.0018)
Wu-Hausman F (1,2608)	= 9.63 (p-value = 0.0019)
ASIZE & PASS	
Durbin (Score) $\chi^2(1)$	= 45.30 (p-value = 0.0000)
Wu-Hausman F (1,2608)	= 45.64 (p-value = 0.0000)
LF & PASS	
Durbin (Score) $\chi^2(1)$	= 36.42 (p-value = 0.0000)
Wu-Hausman F (1,2608)	= 36.57 (p-value = 0.0000)
SEATS & PASS	
Durbin (Score) $\chi^2(1)$	= 35.72 (p-value = 0.0000)
Wu-Hausman F (1,2608)	= 35.85 (p-value = 0.0000)

3.6.2. Proposed Technique

To offset the endogeneity problem, econometric techniques such as the Two-Stage Least-Squares (2SLS) (Jorge-Calderón, 1997) or simultaneous equations approach (Pitfield et al., 2010) have been applied to flight demand modeling. Jorge-Calderón (1997) used the 2SLS to estimate the demand for the international routes of European airlines. Pitfield et al. (2010) suggested a simultaneous equations approach, also known as the Three-Stage Least-Squares Method, to model

ASIZE, **FF**, and **PASS** for nine routes in the U.S. domestic market. Gujarati (2003) suggested the 2SLS as a preferred model in cases of system or full information methods, with no lagged endogenous variables, and not-so-large sample sizes. The 2SLS, as the most common technique in the class of the instrumental variables (IV) estimators for causal relationships, is broadly used by economists to estimate the parameters in the models of linear simultaneous equations to solve the problem of omitted-variables bias in a single equation (Angrist and Imbens, 1995). Wooldridge (2013) concluded that the 2SLS is a more robust and consistent model for addressing endogeneity. The reader can refer to Zellner and Theil (1962) for the details.

The 2SLS technique is chosen to build the model because of the endogeneity between **PASS** and the dependent variables of the model, no lagged endogenous variables, and the medium size of the dataset. This technique runs in two stages. In the first stage, **PASS**, as the endogenous variable, was regressed against all independent parameters, **JFuel**, **LCC**, and **HHI**, and a set of three instrumental factors, **EMP**, **POP**, and **FARE**. In the second stage, a generalized least squares technique was applied to estimate the dependent variables, **FF**, **ASIZE**, and **LF**; **SEATS** by the model parameters; and an estimate of **PASS**.

3.6.3. Model Formulation

A logarithmic transformation of the variables is applied to develop the model predicated on the assumption that the relationship between the variables is non-linear (Pitfield et al., 2010). This format normalizes the model (Ito and Lee, 2005; Wei and Hansen, 2006). Thus, the coefficients are interpreted as the elasticity attributes rather than the typical slope attributes. The proposed regression models can be summarized as follows:

First Stage:

$$\log(P_{it}) = a_P + a_1 \log(Pop_{it}) + a_2 \log(JetFuel_t) + a_3 \log(EMP_{it}) + a_4 \log(Airfare_t) + a_5 HHI_{it} + a_6 \mathrm{LCC}_{it} + a_7 \mathrm{D\_Route}_i + \varepsilon_{it1}$$

Second Stage:

$$\log(F_{it}) = \beta_F + \beta_1 \log(P_{it}) + \beta_2 \log(JetFuel_t) + \beta_3 \mathrm{LCC}_{it} + \beta_4 HHI_{it} + \beta_5 \mathrm{D\_Route}_i + \varepsilon_{it2}$$

$$\log(ASize_{it}) = \gamma_A + \gamma_1 \log(P_{it}) + \gamma_2 \log(JetFuel_t) + \gamma_3 \mathrm{LCC}_{it} + \gamma_4 HHI_{it} + \gamma_5 \mathrm{D\_Route}_i + \varepsilon_{it3}$$

$$\log(LF_{it}) = \delta_A + \delta_1 \log(P_{it}) + \delta_2 \log(JetFuel_t) + \delta_3 \mathrm{LCC}_{it} + \delta_4 HHI_{it} + \delta_5 \mathrm{D\_Route}_i + \varepsilon_{it4}$$

$$\log(Seats_{it}) = \varepsilon_A + \varepsilon_1 \log(P_{it}) + \varepsilon_2 \log(JetFuel_t) + \varepsilon_3 \mathrm{LCC}_{it} + \varepsilon_4 HHI_{it} + \varepsilon_5 \mathrm{D\_Route}_i + \varepsilon_{it5}$$

where (all variables for domestic flight)

F_{it}: Total number of flights on route *i* in period *t*

$Asize_{it}$: Average aircraft size on route *i* in period *t*

LF_{it}: Load Factor rate on route *i* in period *t*

$Seats_{it}$: Available seats on route *i* in period *t*

P_{it}: Total passengers on route *i* in period *t*

$JetFuel_t$: Average cost per gallon in period *t*

$Airfare_t$: Average airfare in period *t*

Pop_{it}: Products of origin-destination states of route *i* in period *t*

EMP_{it}: Products of employment rate of O-D states on route *i* in period *t*

HHI_{it}: HHI on route *i* in period *t*

LCC_{it}: Number of low-cost carriers on route *i* in period *t*

$\mathrm{D\_Route}_i$: Dummy variable for route *i.*

To ensure that the instrumental variables estimates are consistent, this study uses weak instrument test as suggested by Stock et al. (2002), whose output is presented in Appendix 3.5. The null hypothesis of the test was that the instruments used to estimate the endogenous variable are weak.

H0: Instruments that estimate the endogenous variable are weak.

H1: Instruments that estimate the endogenous variable are strong.

From Appendix 3.5, the F-statistics of the Wald test output indicate a value greater than 10 (F [3,2607] = 622), which suggests that the instrumental variables estimated the endogenous variable well. The minimum eigenvalue statistics (MES) was MES = 622 (that is, greater than the 2SLS size of a nominal 5% Wald), which confirms the F-statistics result. The next step based on the model estimation on the mentioned dataset indicates the results and provides some explanations.

3.7.Pooled Results

Table 3.4 summarizes the results in two sections, each representing one stage of the 2SLS.

3.7.1. Pooled results: TSLS- First Step: Flight Demand Model

In the first stage, the coefficients indicate a positive relation among the socio-economic parameters, including **POP**, **EMP**, and **PASS,** which is consistent with previous research (Jorge-Calderón, 1997; Abed et al., 2001; Ito and Lee, 2005). The results show that the effect of POP on PASS is relatively significant on the long-haul routes. On the long-haul routes, a 10% increase in POP would lead to a 12% increase in PASS, considerably higher than a similar rate increase of 4% in PASS for both the short- and the medium-haul routes. The results show the effect of **EMP** is more pronounced on the long-haul routes than the short- and medium-haul routes. A 10% increase of the EMP factor led to an increase of 14%, 12%, and 19% for the short-, medium-, and long-haul routes, respectively.

The estimation indicated that **FARE** negatively affects **PASS**. Flight demand appears to similarly affect the markets. A 10% increase in ticket price led to a 2% decrease in **PASS** in the long-haul market compared with a 1% decrease on the short-haul routes, and 0.3% on the medium-haul routes respectively, albeit the coefficient of medium-haul model is statistically insignificant.

Table 3.4 2SLS outputs

Variables	First Stage		Second Stage							
	Passenger		Flight Frequency		Aircraft Size		Load Factor		Available Seats	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Short-Haul Routes										
Log (PASS)	NA	NA	0.226	3.75	0.488	10.14	0.284	6.15	0.713	15.42
D_LCC	0.016	6.59	0.026	8.45	-0.023	-9.09	-0.004**	-1.47	0.004**	1.52
Log (Jet Fuel)	0.003**	0.23	0.030	2.51	0.036	3.78	-0.068	-7.26	0.067	7.20
HHI	-0.098	-4.29	-0.064	-2.49	0.033**	1.59	0.031**	1.59	-0.032**	-1.60
Instrumental Variable										
Log (EMP)	1.335	11.93	NA	NA	NA	NA	NA	NA	NA	NA
Log (FARE)	-0.116	-5.81	NA	NA	NA	NA	NA	NA	NA	NA
Log (POP)	0.410	13.78	NA	NA	NA	NA	NA	NA	NA	NA
Routes Dummy	Please see the Appendix 3.6									
Intercept	-4.486	-7.03	2.289	6.60	-0.561	-2.02	0.278**	1.05	1.733	6.49
Observation	791		791		791		791		791	
R-Squared	0.994		0.988		0.960		0.745		0.995	
Medium-Haul Routes										
Log (PASS)	NA	NA	0.724	13.57	-0.079*	-1.77	0.357	8.89	0.643	16.02
D_LCC	0.037	13.27	-0.013	-3.59	0.025	8.09	-0.012	-4.29	0.011	4.27
Log (Jet Fuel)	-0.023*	-1.95	-0.020*	-1.88	0.032	3.49	-0.011**	-1.38	0.011**	1.36
HHI	0.017**	0.76	-0.276	-13.22	0.169	9.66	0.106	6.79	-0.106	-6.78
Instrumental Variable										
Log (EMP)	1.205	12.10	NA	NA	NA	NA	NA	NA	NA	NA
Log (FARE)	-0.032*	-1.67	NA	NA	NA	NA	NA	NA	NA	NA
Log (POP)	0.435	14.08	NA	NA	NA	NA	NA	NA	NA	NA
Route Dummy	Please see the Appendix 3.6									
Intercept	-5.286	-9.01	-0.707	-2.90	2.464	12.07	0.232*	1.26	1.762	9.60
Observation	1032		1032		1032		1032		1032	
R-Squared	0.994		0.993		0.649		0.445		0.996	
Long-Haul Routes										
Log (PASS)	NA	NA	0.778	37.98	0.237	12.42	-0.008*	-0.66	1.001	82.32
D_LCC	-0.006*	-1.25	0.011	3.64	-0.006	-2.12	-0.005	-3.00	0.005	2.94
Log (Jet Fuel)	0.135	5.48	-0.076	-4.58	0.045	2.99	0.030	3.02	-0.029	-3.02
HHI	-0.125	-3.49	-0.079	-3.23	0.039	1.75	0.041	2.81	-0.039	-2.70
Instrumental Variable										
Log (EMP)	1.820	11.32	NA	NA	NA	NA	NA	NA	NA	NA
Log (FARE)	-0.179	-4.33	NA	NA	NA	NA	NA	NA	NA	NA
Log (POP)	1.215	23.06	NA	NA	NA	NA	NA	NA	NA	NA
Route Dummy	Please see the Appendix 3.6									
Intercept	-17.38	-21.81	-1.094	-10.23	1.15	12.80	1.93	29.95	0.066	1.03
Observation	811		811		811		811		811	
R-Squared	0.980		0.987		0.802		0.478		0.996	

*p-value>0.05

**p-value>0.10

The results indicated the **JFuel** parameter as an insignificant factor in **PASS** model in the short- and medium-haul routes. Notably, a higher **JFuel** resulted in a higher **PASS** on the long-haul routes**,** which correlates with the price of oil products and its final effect on economic activities on the long-haul routes. The long-haul routes are related to the two industrial cities of Perth and Darwin.

According to Ghalayini (2011), higher prices of crude oil and petroleum products would lead to higher rates of economic growth for the oil exporting regions or countries. Perth and Darwin are known as regions with rich natural resources and a strong mining and oil industry in Australia. Therefore, it is to be expected that the higher price of crude oil and its substitutions would lead to stronger economic growth in these regions. As an evidence for this statement, this study estimates the employment rate on jet fuel price for eight main cities in Australia. Table 3.5 presents the effect of jet fuel price, as a proxy for oil price, on employment rate, as a proxy for economic growth, for the eight main cities. The results are meaningful as Perth and Darwin captured the highest coefficients compared to the other cities. Thus, the significance of the jet fuel price on the passenger model is due to the economic and industrial characteristics of Perth and Darwin. In fact, these cities are the destination of the business travelers. So, a higher oil price leads to stronger economic growth that consequently leads to more business trips to these cities.

Table 3.5 Effect of jet fuel price on employment rate

City	Melbourne	Adelaide	Brisbane	Sydney	Canberra	Hobart	Darwin	Perth
Coeff.	0.45	0.45	0.48	0.50	0.68	0.77	1.04	1.11

The estimations reveal a positive effect of **LCC** in stimulating **PASS** on the short- and medium-haul routes. A 10% increase in **LCC** led to a 1.6% and 3.7% increase in demand on the short- and medium-haul routes, respectively. This might be because of the LCCs' characteristic to offer lower fares than those of legacy airlines (Belobaba et al., 2009, p.122) that, in turn, results in higher demand. However, the data indicate no effect of **LCC** in boosting **PASS** in the long-haul market, possibly due to less participation of low-cost airlines in the long-haul market. The **HHI,** an indicator of airline competition, shows a positive effect on flight demand for the short- and long-haul routes. A 10% increase in **HHI** results in 10% and 13% increases in flight demand in the short- and long-haul routes, respectively. The model outputs indicate competition as an insignificant factor on passenger demand in the medium–haul market.

3.7.2. Pooled results: TSLS- Second Step

In the second stage of the 2SLS, this study separately develops the models **FF**, **ASIZE**, **LF**, and **SEATS** using **PASS**, **JFuel**, **LCC**, and **HHI**.

3.7.2.1.TSLS- Second Step: Flight Frequency Model

The frequency model fitted best as its R^2 was greater than 0.95. **PASS** plays a crucial role in flight frequency on the different routes although to different degrees. A 10% increase in **PASS** led to a 2% increase in **FF** in the short-haul, 7.1% in medium-haul, and a 7.7% in the long-haul market, respectively. **JFuel** demonstrated different effects regarding flight distance. Table 3.4 demonstrates that, in the short-haul market, an increase in **JFuel** positively affects both **PASS** and **FF**. This positive effect seems to correlate with the price of oil products and their effects on flight and surface transportation in short-haul markets where competing modes of transportation are available for passengers (Belobaba et al., 2009, p.58). In fact, higher oil prices directly result in higher prices for oil products, such as jet fuel and gas. However, due to airline competition and the cap on increasing ticket prices, the net effect of this additional expense seems less for the users of aviation transport than for the surface transport modes such as cars, trains, and buses.

The above effect is reversed for the medium- and long-haul routes. A 10% increase in **JFuel** led to a 0.19% and 0.73% decrease on the medium- and long-haul routes respectively. Airlines tend to provide the required flight capacity with less flight frequency but with larger aircraft. Airlines have historically applied such a strategy in addition to their hedging policies to offset the increases in **JFuel**. **LCC** records a positive effect on **FF** of the city-pair routes on the short- and long-haul routes. A 10% increase in **LCC** led to an increase of 2.6% and 1.1% in **FF** on the short- and long-haul markets respectively. However, this effect is negative for the medium-haul route; a 10% increase in **LCC** results in a 1.3% decrease in **FF**.

The estimation output shows airline competition in terms of the **HHI** increases in **FF** on all routes under study, particularly for the medium-haul market. A 10% increase in **HHI** led to a 7%, 31%, and 8% increase on the short-, medium-, and long-haul routes, respectively. This result supports the findings of Wei and Hansen (2005) about the relation of flight frequency and airline competition.

3.7.2.2.TSLS- Second Step: Aircraft Size Model

The aircraft size model indicates a positive effect between **PASS** and **ASIZE** in the short- and long-haul markets. A 10% increase in **PASS** leads to a 5% and 2% increase in aircraft size in the short- and long-haul markets, respectively. However, airlines seem to be more flexible in applying larger aircraft on the short-haul market compared to the long-haul market due to the constraints of airport capacity on the routes under study. Notably, the model indicates a negative effect between **PASS** and **ASIZE** for the medium-haul market. This negative effect stems from the greater elasticity of **FF** than **SEATS** on **PASS** changes in the medium-haul market. In fact, **ASIZE** is computed as **SEATS** divided by **FF**. With respect to the model estimations, a 10% increase in **PASS** led in a 7.1% increase in **FF** and a 6.3% increase in **SEATS**, resulting in a negative effect of **PASS** changes on **ASIZE** in the medium-haul market.

JFuel scales up the **ASIZE**. In fact, jet fuel inflations led airlines to perform upgauging, in terms of adding more seats on existing jets or replacing smaller aircrafts with larger ones, which generally leads to a lower operating cost per seat (Belobaba et al., 2009, p.135). This finding supports the conclusions of Ryerson and Hansen (2013) about the impact of fuel costs on airline operating policies. For example, a 10% increase in **JFuel** results in a 0.35% increase in aircraft size in all markets. According to Belobaba et al., 2009, low-cost carriers typically operate smaller aircrafts in shorter distances. The estimation indicates that **LCC** decreases **ASIZE** on the short- and long-haul routes in the market. The presence of the low-cost carriers on the short- and long-haul routes decreases **ASIZE** by 2.33% and 0.6% respectively. In contrast, a 10% more participation of the low-cost carriers led in an increase of 2.5% in **ASIZE** on the medium-haul routes. Notably, the competition among the airlines results in a smaller **ASIZE** in all markets. More competition between airlines, as shown by a 10% decrease in **HHI**, led to an increase of smaller aircrafts by 3.3%, 18.4%, and 4% in the short-, medium-, and long-haul routes, respectively. However, the estimation is statistically insignificant for the short-haul market.

3.7.2.3.TSLS- Second Step: Load Factor Model

In the load factor model, the effect of **PASS** is positive but arguably minimal; a 10% change in **PASS** resulted in an increase of 2.7% and 3.4% in **LF** in the short- and medium-haul markets respectively. This effect is statistically insignificant for the long-haul market. **LCC** shows a small negative impact on **LF** in the medium- and long-haul routes, but it is an insignificant factor in the short–haul market. Similarly, the significance of **JFuel** is small, with a negative effect in the short-haul market, and positive on the long-haul routes. The effect is insignificant for the medium-haul routes. Like the aircraft size model, the **HHI** reduces **LF** in all the markets, particularly on the medium-haul routes. More competition, through a 10% decrease in **HHI,** reduces **LF** by 11%.

However, the R^2 of the Load Factor model is relatively small, except in the short-haul market, which renders the results unreliable for interpretation. In fact, with respect to the estimation, it can be interpreted that the airlines have not been concerned with **LF** as a key element in capacity planning in the Australian domestic market, particularly for the medium- and long-haul markets. This finding is relatively consistent with the discussion of Jorge-Calderón (1997) about the significance of load factor in air traffic management. As discussed by Jorge-Calderón (1997), while flight frequency has frequently proven to be a significant driver in passenger demand modelling, the prior studies have econometrically shown an ambiguity about the significance of load factor in air traffic management.

3.7.2.4.TSLS- Second Step: Available Seats Model

In the final equation, in the Available Seats model, **PASS** played a key role in determining flight capacity, as expected. A 10% increase in **PASS** resulted in a 7%, 6% and 10% increase in **SEATS** on the short-, medium- and long-haul routes, respectively. **JFuel** recorded a slight positive effect on **SEATS** in the short-haul market but slightly negative for the long-haul flights. The results suggest **JFuel** to be insignificant on **SEATS** in the medium-haul routes. **LCC,** with low coefficients in the model, presented as a non-significant parameter for estimating **SEATS**. This factor recorded a small positive effect on **SEATS** with a highest change of 1% in SEATS on the medium-haul routes with respect to an increase of 10% in **LCC.** In contrast, **HHI** recorded a positive effect on **SEATS** for all origin-destination routes. More competition, in terms of a 10% decrease in **HHI**, led in an increase of 3%, 11%, and 4% in **SEATS** on the short-, medium-, and long-haul routes, respectively.

3.8.Summary

Australia is heavily reliant on its air transportation due to the spatial distribution of the urban centers across the country. This dependency appears to be growing with population growth. The purpose of this study was to provide insights into Australia's domestic aviation market and to understand the drivers on both sides of the supply-demand equilibrium. Four variables of flight frequency, aircraft size, load factor, and available seats were defined in this chapter as "capacity algorithm", to investigate the airline capacity decisions regarding the domestic routes. The number of air passengers and airfares, combined with two socio-economic factors, namely population and employment rate, were used to build the model on the demand side. Competition between airlines, jet fuel price, and participation of low-cost carrier were also added to the supply side to provide a comprehensive framework for modeling. As these parameters appear on both sides of the supply-demand equilibrium, this study enables to identify the drivers influencing the airline capacity decisions in the domestic market. On the bilateral interaction among the variables on both sides of the equilibrium, a two-stage least-squares method was applied to analyze the cross-sectional time-series data of the airlines. The results suggest that a higher demand for flights primarily results in increased flight frequency rather than increased aircraft size or load factor, which is consistent with the literature (Pitfield et al., 2010). The load factor is shown to be an insignificant variable in capacity planning of the airlines, particularly on the medium- and long-haul routes, albeit significant in capacity planning in the high-demand short-haul routes.

The results suggest that the airlines apply tailored approaches in capacity planning, with respect to the passenger demand changes, for the short-, medium-, and long-haul routes. In the short-haul market, airlines are more flexible in the choice of aircraft. As a result, the elasticity of the flight frequency is smaller than that of aircraft size in the short-haul market with respect to the passenger demand. By contrast, flight frequency features as the key player of capacity planning for the medium- and long-haul routes. The results indicate that the airlines responded to the demand inflation in the medium-haul market with more flights and used the same or even smaller sized aircrafts, leading to a negative effect of passenger demand on aircraft size. In the long-haul routes, both flight frequency and aircraft size are significant in capacity planning, albeit with less elasticity of aircraft size on passenger demand compared to that of the short-haul market.

Contrary to the findings of Ito and Lee (2005) in which the jet fuel cost was found to be an insignificant factor in the airline demand model, this factor is shown to be a driver on both sides of the supply-demand equilibrium of Australia's domestic market. On the short-haul routes, the increase in oil price and related products arguably stimulated flight demand and resulted in an increase in flight frequency, possibly due to the higher negative elasticity of surface transportation demand to the oil price inflation compared to air travel. Further research is required to investigate the inflation impact of oil price and its related products on air and surface transportation. Furthermore, the higher jet fuel prices scaled up aircraft size on all flight routes. Notably, this study highlighted a significant effect of jet fuel cost on passenger demand on the long-haul routes.

This can be viewed with respect to the industrial specification of the routes in the long-haul market. In this market, higher jet fuel costs led to fewer flights, larger aircraft size, higher load factors, and fewer available seats.

Low-cost carriers played a key role in the short-haul routes. For the period under study, low-cost carriers stimulated flight demand, increased flight frequency, and reduced aircraft size in the short-haul market. The results also indicate the positive impact of low-cost carriers on flight demand. However, this factor affects capacity planning of the airlines differently in the medium market compared to the short-haul routes. In contrast, the participation of the low-cost carriers on the long-haul routes was non-significant. This effect most likely stemmed from the low-cost carriers' policy of focusing on the short-haul direct flights. Competition among the airlines enhanced flight demand and resulted in more flights, smaller aircraft size, and lower load factors.

This chapter has sought to reveal a general picture of the Australian domestic aviation market and the main players in the supply-demand equilibrium. As mentioned, the econometric estimation was able to represent a holistic snapshot of the Australian market and its key players. However, some ambiguity surrounding the interpretation of some parameters in the markets remain. This requires further investigation. Therefore, moving forward, scholars in this area can examine the specific origin-destination routes to explain the primary drivers in the market.

Chapter 4

Identification of the impact of airlines' capacity decisions on flight delay

4.1. Introduction

This chapter is to identify the key determinants on flight delay as one of the key players of supply-demand equilibrium of the flight market. This chapter begins with describing the flight delay phenomenon, and its status in Australian domestic flight market. Next the model parameters are introduced, followed by the data description. Section 4.6 provides methodological framework in terms of model specification, proposed technique, and model formulation. It then discusses the pooled results of the flight delay model. The final section of this chapter provides a summary review of the econometrical analysis of flight delay model.

4.2.Background

Flight delays can affect airlines in several ways, namely, more flight expenditure and customer dissatisfaction. Consistent flight delays might also lead to governments setting new regulations. While the airlines point to the weather and ineffective air traffic control systems as the key reasons for flight delays, the airlines are also at fault for scheduling flights above their capacity (Pai, 2010). The significant increase in incidents of flight delays has raised regulatory concerns in the last decade. Regulators have already imposed strict measures on the airlines to avoid flight delays and cancellations so as to protect the passengers.

Flight delays are also financially costly. The total yearly cost of flight delays in the U.S. aviation market is estimated at over $30 billion; the amount attributable to the airlines was $8.7 billion in 2007 (Ball et al., 2010). Peterson et.al (2013) reported that a 10% reduction in flight delays would increase US net welfare by $17.6 billion (Peterson et al., 2013). For the airlines, flight delays lead to additional expenses in staffing, jet fuel, and aircraft maintenance. As such, initiatives are in place to curb flight delays and lift capacity, including developing new runways, better runway layouts, upgraded air traffic control facilities, and air traffic control procedures. For example, United Airlines saved $1.6 million during the first quarter of 2004 by applying a flight delay projection model (Abdelghanya et al., 2004).

Flight delays and cancellation affect both airlines and air travelers. Airlines suffer a loss in passenger loyalty and consequently market share. Flight delays not only increase the costs (Zou and Hansen, 2014), the time lost due to a delay or cancellation would also lead to productivity loss for both the traveler and the firm (Peterson et al., 2013).

Without upgrading the airport infrastructure and developing effective mechanisms to manage air traffic, the cost of flight delays will rise (Peterson et al., 2013). While there are several empirical studies that investigate the characterization of flight delays and airline response (Muelle and Chatterji, 2002; Zou and Hansen, 2014), there is no known empirical study on flight delays in the Australian domestic aviation context. Further, after the domestic aviation market was deregulated in 1990, the low-cost carriers have since penetrated the market (Nolan, 1996). Today, Jetstar and Tigerair are the dominant low-cost carriers in Australia.

This chapter investigates the drivers of flight delays by using the Australian domestic aviation market to appreciate the role of airline-related factors on this issue. Further, unlike previous studies which focused on a micro level data analysis, this study analyzes the macro level data to identify the airline and non-airline related factors of flight delays. The dependent variable is the flight delays during departure. Various variables, including airline capacity decisions and route-specifics, are used to develop the regression models.

As flight delays are known to be an indicator of the performance assessment of airlines (Wieland, 1997; I.D., 2019), this study examines how the flight delay rate may differ between the low cost carriers and legacy airlines.

4.3.Case Study Context: Australian domestic market

Since the past decade, flight delays[6] have captured the attention of the media, scholars, and even regulators across the world (Britto et al., 2012). In Australia, of the 5.7 million flights scheduled in the domestic aviation market from January 2005 to December 2015, 915,000 flights had experienced individual delays by at least fifteen minutes; this translates to 16% of all flights annually (BITRE, 2006 - 2016). According to the Department of Infrastructure and Regional Development (DIRD) (BITRE, 2018), the flight delays in arrivals and departures contribute to 17.3% and 16% of the total arrivals and departures, respectively. Indeed, the data reveal an uptrend in flight delays in recent years. For example, while flight delays in departure were 16.2% for 2016-2017 the figures jumped to 18% in 2017-2018. Some research already suggest that the delay rates will continue to increase due to population growth and more air travel (Zou and Hansen, 2014). However, flight delays may depend on other factors such as the airline's operating model. Figure 1 shows the trend of the average flight delays for the four dominant Australian domestic airlines from 2004 to 2015. In 2008 and 2015, the airlines recorded the highest and lowest average rates of flight delay. Percentagewise, there has been a reduction of 72% in flight delays between 2008 and 2015, albeit not uniformly for all four airlines. As shown in Figure 4.1, the flight delays during this period have declined for the legacy carriers Qantas and Virgin. The reasons can be attributed to the improved traffic and operations systems used by these airlines. However, there is no sign of improvement in the flight delays for the low-cost carriers, Jetstar and Tigerair.

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[6]. A flight delay is defined as "the number of flights departing the gate with a delay of more than 15 minutes after the scheduled departure time shown in the carrier's schedule for a given route each month (http://bitre.gov.au/)".

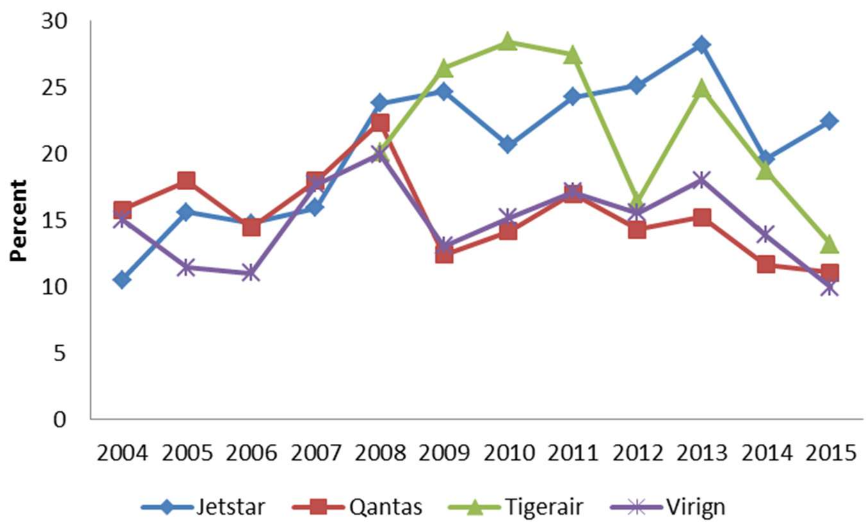

Figure 4.1 Pattern of annual flight delays for four Australian domestic airlines

Today, economies, such as New Zealand, the US, Indonesia, and the European Union (EU), have clear guidance and regulations on passenger compensation arising from flight delays and cancellations. For example, the U.S. Department of Transportation (DOT, 2015) implemented regulations to limit tarmac delays to three hours and imposed fines on the airlines for longer delays. In the EU, there is legislation to compensate passengers for any flight delay and cancellation. Passengers are compensated if their flights arrive late by more than three hours. This compensation varies depending on the flight distance or delay circumstances (EUROPA, 2004). Currently, from a regulatory perspective, Australian airlines do not provide a guarantee to their flight timetable. According to CHOICE research, 76% of the flight travelers in domestic Australia prefer to pay more airfare to have an EU-like legislation covering flight delays (Castle, 2017).

4.4.Parameters

Table 4.1 describes the model parameters. From the DIRD information (http://bitre.gov.au/), a flight delay is defined as "the number of flights departing a gate at least 15 minutes after the scheduled departure time shown in a carriers' schedule for a given route each month". Therefore, for the purpose of this study, for any given route, flight delays during a departure is employed as the model's dependent variable, which is computed as the number of delayed flights during a departure divided by the number of scheduled flights of each city pair of a given route and time window, respectively.

Airlines determine the available capacity of a route through three variables: flight frequency, type of aircraft, and flight load factor (Sibdari et al., 2018). Airline capacity decisions also affect the quality of the flight service and their operating costs. These factors directly affect airline operations and traffic volume that would influence the rate of flight delays (Jorge-Calderh, 1997). From the monthly data reported, the average air passenger load factor can reflect the congestion level of the routes which is set as the level of a route's available capacity occupied by the required air demand. Capacity decisions include flight frequency, aircraft size, and passenger load factor, which, in turn, are influenced by the airline's capacity policies and constraints. The number of passengers is critical to passenger aviation demand as this variable influences an airline's capacity decisions (Ito and Lee, 2005; Chi and Baek, 2013). The endogenous relationship between the number of passengers and an airline's capacity decisions in the Australian domestic air market has previously been discussed in the literature (e.g., Mohammadian et al., 2019a). Furthermore, the initial analysis on the data indicates a high level of correlation between demand and flight frequency. This study ignores the demand factor to avoid any unnecessary complexity in the modeling and possibly bias the results. However, as discussed later, three passenger regressors, namely, population, employment rate, and airfare are used to model flight delays.

Table 4.1 Description of parameters

Term*	Definition	Type	Data source
Flight Delay in Departure (%)	Number of flight delays in departure divided by number of scheduled flights	Monthly/OD	DIRD, Domestic on-time performance reports (http://bitre.gov.au/)
Flight Frequency	Total number of flights for a given route each month.	Monthly/OD	DIRD, Domestic aviation activity reports (http://bitre.gov.au/)
Average Aircraft Size	Computed as the number of available seats divided by flight frequency for a given route and time period	Monthly/OD	DIRD, Domestic aviation activity reports
Load Factor (Congestion rate) (%)	Computed as a ratio of total passenger to the total available seats for a given route and time period	Monthly/OD	DIRD, Domestic aviation activity reports
Distance (km)	Airport to airport non-stop distance for a given route	OD	DIRD, Australian air distance reports (http://bitre.gov.au/)
HHI	Hirschman- Herfindahl Index on a route each month	Monthly/OD	DIRD, Domestic on-time performance reports
Jet Fuel Price	Average monthly fuel price in US airline industry (U.S. Gulf Coast kerosene-type jet fuel spot price fob)	Monthly/World	U.S. EIA (http://www.eia.gov/)
Low-cost Carrier Participation (LCC)	Total number of flights flown by low cost carriers divided by total flight on a route each month	Monthly/OD	DIRD, Domestic aviation activity reports (http://bitre.gov.au/)
JFuel_ LCC	Computed by multiplying average monthly fuel price with LCC	Monthly/ OD	--
LF_ LCC	Computed by multiplying load factor with LCC	Monthly/ OD	--
Airfare	Australian Domestic Airfare - real full economy index (Ref. month: July 2003) for a given period	Monthly/Australia Domestic Market	DIRD, Domestic air fare index (http://bitre.gov.au/)
Population (billion)	Computed as the product of Population of each city pair for a given route and time period	Monthly/State	ABS (http://www.abs.gov.au/)
Employment Rate	Computed as the product of Employment rate (%) of each city pair for a given route and period		Department of Employment (http://imip.gov.au/)

*Information covers both directions of each city pair for a given route

Jet fuel price is the main and less-predictable source of operating costs for airlines (Carter, 2006). Studies have established jet fuel price to negatively affect an airline's operation and services (Ito and Lee, 2005; Borenstein and Rose, 2014) and increase flight cancellations and delays (Stock, 2013). Furthermore, this factor may be a proxy to reflect the effects of significant national and world incidents such as Ansett Australia's collapse in 2001, the Sydney Olympic Games in 2000 or the tragedy of September 11, 2001, and the global economic downturn 2007-2009. Due to the importance of jet fuel price on an airline's operation (Sibdari et al., 2018), This study uses this parameter to identify the effect of airline operating costs on flight delays.

Route-related factors: This study introduces a set of factors that explains the route specification. These factors are distance, participation of low-cost carrier, and airline competition on a route. These factors may influence the aircraft movement on the scheduled flights. Distance is the most common locational factor that influences both flight demand and airline operations (Russon and Riley, 1993). The participation of the low-cost carriers, as previously discussed, affects airline services (Barrett, 2004; Pels, 2009). The low-cost carrier participation rate is estimated in this study by the number of flights flown by the low-cost carriers divided by the total number of flights for a given route per month. Jetstar and Tigerair are the main low-cost carriers in the Australian domestic aviation market. Low-cost carriers apply different operating models that may influence flight delays. For example, Jetstar as a low-cost carrier offers direct flights that are operationally different from the hub-and-spoke networks used by Qantas as a legacy carrier.

Airline competition reflects a significant effect on flight demand in air transportation (Barrett, 2004; Pitfield et al., 2010; Gillen and Hazledine, 2015). Gillen and Hazledine (2015) suggest that stiff competition yields better flight service. The Hirschman–Herfindahl Index (HHI), defined in section 3.4, is applied as an indicator of airline competition in the routes examined.

Weather-related factors: According to the Bureau of Transportation Statistics (BITRE 2016), weather-related factors account for 40% of the total delay instances (Choi et al., 2016). Prior studies (Abdelghanya et al., 2004; Abdel-Aty et al., 2007) highlight the cyclical and seasonal impacts of these factors on flight delays in an airport. To control for the effects of inclement weather or weather-related factors, this study initially applied the factors such as average low temperature and average rain. However, the monthly data are the only available data being used in this study to identify the impact of macro-level airline-related factors on flight delays. Therefore, based on the initial analysis, the weather-related factors cannot completely address the effect of weather changes on flight delays. Nevertheless, in the treatment of the weather-related factors, the seasonal and weather-related components were removed from analysis using a filter of seasonal adjustment known as the X11 style technique. This technique is based on a moving average procedure first described by Macaulay (1931) and cited in Ladiray & Quenneville (2001). As a result of applying the seasonally adjusted data, this study assumes that the effect of periodic and seasonal factors is already being offset and no weather-related factor is required in the modeling. Therefore, the percentages computed as the increase or decrease on flight delay on a specific parameter only reflects the relative significance of that parameter compared to the other model factors. For example, a 10% increase in flight frequency only reflects the relative impact of flight frequency on flight delays compared to the other model parameters excluding the weather-related factors.

Interaction variables: Airlines react differently to external changes such as macro-economic factors or air market changes that may influence flight delays. To understand more about the impact of the low-cost carriers' performance on flight delays, this study introduces two interaction variables. The variable of JFuel_ LCC, defined as the product of the jet fuel price and low-cost carrier participation rate, is used to show how effectively the low-cost carriers have managed their operations in a regime of jet fuel inflation. The second interaction variable, LF_LCC, is identified by multiplying the load factor with the low-cost carrier participation rate. Higher load factors or congestion levels may render more flight delays. Therefore, in the cases with higher load factors, the question is, compared to the legacy airlines, how effectively the low-cost carriers can manage their operations to mitigate the flight delays. To avoid a high multi-collinearity between the interaction variables and the parameters, this study applies mean centering on the initial parameters and use the outputs to create the interactions. This step eliminates the correlation between the original parameters and the interactions (Jaccard and Turrisi, 2003).

4.5.Data

The available data cover 21 major monthly flight route records of all the domestic airlines which include Jetstar, Tigerair, Qantas, Virgin, and the other carriers[7]. The routes link eight state capitals in Australia. Figure 4.2 presents the routes targeted in this research, categorized based on the total number of flights in the year 2015. The dataset comprises the city-pair monthly data from January 2004 to December 2015. The routes are chosen as they are the higher-demand routes in Australia, and several airlines compete on these routes.

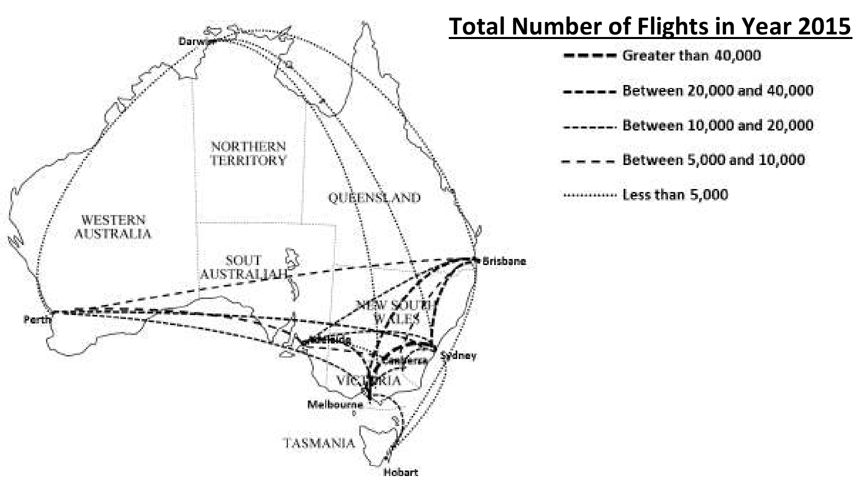

Figure 4.2 Targeted domestic origin-destination flight routes[1]

[7]. include QantasLink, Virgin Australia – ATR/F100 Operation, Virgin Australia Regional Airlines, and REX.

For the datasets, this study relies on the data of two public-sector agencies, the Australian Bureau of Meteorology (BOM) and the DIRD. All data were seasonally adjusted by a filter method of seasonal adjustment known as the X11 style technique (Ladiray & Quenneville, 2001) to reflect the industry's pattern. Due to the unavailability of the jet fuel price information in the Australian domestic aviation market, the monthly information of the U.S. Gulf Coast kerosene-type jet fuel spot price was applied to address this factor in the proposed model. This proxy is applicable as jet fuel price is a universal commodity for which its price influences all economies including Australia. Table 4.1 describes the data sources of the parameters. Appendix 4.1 shows the descriptive statistics of the variables.

4.6.Methodological framework

4.6.1. Model Specification

The dataset is characterized as a cross-sectional time-series. Therefore, using an ordinary least square method (OLS) may result in a biased and inconsistent estimation (Wooldridge, 2010, p.247). As for the data specification, two popular techniques of panel data analysis, fixed effects and random effects, were applied to estimate the regression models (Maddala and Lahiri, 1992). Using these methods can eliminate bias and improve efficiency (Wooldridge, 2010, p.247). The panel specific effects are assumed to be correlated with the independent variables in the fixed effects model, while uncorrelated to the other covariates in the random effects model. The more effective model can be selected by applying a Hausman specification test (Hausman, 1978). The Hausman specification test is an effective approach to identify the appropriateness of either of these two techniques with the following null hypothesis:

H_o: The difference of the coefficients of the fixed and random-effects models is not systematic.

If H_o is not rejected, then the random effects model is more effective than fixed effects model to estimate the model's coefficients (Wooldridge, 2010, p.288).

Appendix 4.2 presents the Hausman-test results for the flight delays model. The test rejects H_o ($p = 0.002$). So, the fixed effects model is identified as a more effective model to estimate the coefficients than the random effects model. However, as the model includes distance, as a time-invariant variable, the fixed effects model is not applicable in this study as this model is unable to address the time-invariant variables (Wooldridge, 2010, p.265). Further, a bilateral relation, which is known as endogeneity, has been discussed between flight delays and the elements of capacity decisions in the literature (Jorge-Calderh, 1997; Pitfield et al., 2010). Endogeneity causes a loop of causality between the model parameters and variables (Wooldridge, 2013), making the use of OLS methods ineffective for modeling (Pitfield et al., 2010).

4.6.2. Proposed Technique

Hausman and Taylor's instrumental variables estimator is applied in this research to address both the endogeneity effect and the time-invariant factors (Hausman and Taylor, 1981). Hausman and Taylor's estimator provides an approach for overcoming the shortcoming of the random effects model while including the time-invariant characteristics. The Hausman-test assumes that airline–related and route-related factors are correlated with the unobserved individual effect. Therefore, the model is rewritten as follows:

$$\log(Delay_{it}) = Constant + \alpha X_{1it} + \beta X_{2it} + \gamma Z_{1i} + \delta Z_{2i} + c_i + \varepsilon_{it}$$

where X_{1it} is the vector of the explanatory time-variant airline-related parameters that are assumed to be uncorrelated with c_i; X_{2it} is the vector of the explanatory time-variant route-related parameters that are assumed to be uncorrelated with c_i; Z_{1i} is the vector of explanatory time-invariant airline-related parameters, uncorrelated with c_i; Z_{2i} is the vector of explanatory time-invariant route-related parameters, uncorrelated with c_i. c_i is added to the model that shows the unobserved panel-level random effects, presumed to have zero mean and finite variance σ_μ^2 that are independently distributed over the panels. In this model, ε_{it} is an idiosyncratic error that is assumed to have zero mean and finite variance σ_ϵ^2 distributed Normally over observations (Greene 1981).

The Hausman and Taylor estimator requires instrumental variables that are correlated with the endogenous variables, and not directly related to flight delays. Airfare combined with two socio-economic factors, population, and employment rate, are added as instruments to the model. The socio-economic factors were identified in prior studies as the primary parameters that stimulate flight demand (Ito and Lee, 2005). Airfare is a significant explanatory variable in flight demand modeling. All other parameters being equal, a higher airfare leads to weaker flight demand. As the monthly route-level data on airfares are not available, the economy-class airfare index in the Australian domestic aviation market is taken as a proxy for this parameter.

4.6.3. Model Formulation

A statistical model is now formulated to identify the effect of the different factors on flight delays in the targeted routes of the Australian domestic aviation market. A log-linear form is applied to approximate the non-linear relationship between flight delays and the explanatory variables as discussed in the literature (Pitfield et al., 2010). The regression model is set as:

$$\log(Delay_{it}) = a_P + a_1 \log(FF_{it}) + a_2 \log(LF_{it}) + a_3 \log(Asize_{it}) + a_4 \mathrm{Dist}_i + a_5 \log(HHI_{it}) + a_6 LCC_{it} + a_7 \log(JetFuel_t) + a_8 JFuel\_LCC_{it} + a_9 \mathrm{LF}\_LCC_{it} + c_i + \varepsilon_{it}$$

where the subscripts i and t denote route i and period j, respectively. The coefficient a_P estimates the model intercept, c_i is route i's unobserved effect, and ε_{it} is the error term. The other variables are defined below:

$Delay_{it}$: Portion of scheduled flights delayed on route i in period *t.*

F_{it}: Total number of flights on route i in period *t.*

$Asize_{it}$: Average aircraft size on route i in period *t.*

LF_{it} : Load factor on route i in period *t.*

LCC_{it}: Participation of low-cost carrier on route i in period t

Dist_i: Airport to airport non-stop distance on route *i.*

HHI_{it}: HHI on route i in period *t.*

$JetFuel_t$: Average cost per gallon of jet fuel in period t

The model is implemented in two steps. The first step analyzes the effects of the airline-related and route-related factors on flight delays. In the second step, the interaction variables, JFuel_ LCC and LF_LCC, are added to the model to examine the performance of the low-cost carriers on flight delays. JFuel_LCC and LF_LCC are found by multiplying $\log(JetFuel_t)$ and $\log(LF_{it})$ with LCC_{it}, respectively. This step seeks to compare the performance of the low-cost carriers against the legacy airlines, based on jet fuel price and route congestion (load factor).

4.7.Pooled results

4.7.1. Pooled results: Main effects

Table 4.2 presents the results of the Hausman-Taylor regression. The first run of the model includes the main factors that include the airline-related and route-related parameters. The variables of capacity decision have a positive effect on flight delays, albeit in different degrees. For the flight frequency variable, the coefficients suggest a positive relationship between flight frequency and flight delays. Holding the other variables constant, a 10% increase in flight frequency is expected to increase flight delays by 2.3%. This result concurs with the findings of prior micro-level studies, which suggest that more flights intending to depart can lead to flight bunching and worsen the propagation effect of the flight delays. This is an interesting finding as more frequent flights were initially thought to provide more backup options for delayed flights and passengers. However, the result shows the opposite to this initial notion. In fact, sometimes the capacity of the airport is not able to support the case for several aircraft repairs due to airport facility manning issues. Besides, more flights mean more take-offs and landings, so the interarrival time between flights is reduced and the margin of error for a scheduled take-offs or landings becomes tighter. So, what this suggests is that a prolonged delay by the first flight will have a snowball effect on subsequent flights and the delay propagation effect kicks in. In this instance, the induced effect is greater than the intended benefit. Thus, higher flight frequency results in a shorter time buffer between flights, leading to a prolonged propagation effect of the initial delay. However, this trend is not sticky between airlines, as shown in Figure 4.3. From Figure 4.3, which shows the average flight delay compared to the flight frequency for the four dominant airlines, there has been a drop in the flight delay rates of the airlines, except for Jetstar, despite the total average growth in flight frequency, especially in the past five years.

Table 4.2 Results of Hausman-Taylor regression

Variable	Main effects		Interaction effects	
	Est.	t-stat	Est.	t-stat
Intercept	-9.897	-7.49	-9.615	-7.140
Endogenous Time-Variant				
Flight Frequency	0. 245	5.55	0.246	5.590
Aircraft Size	0.195	4.80	0.196	4.870
Load Factor	1.215	13.12	1.216	13.110
HHI	0.140	3.770	0.144	3.850
LC Participation	0.066*	2.010	0.064*	1.95
Exogenous Time-Variant				
Jet Fuel	0.491	13.620	0.522	11.64
Airfare (instrument)	-0.256	-4.69	-0.260	-4.75
Population (instrument)	0.089*	2.10	0.040**	0.910
Employment Rate (instrument)	1.668	6.060	1.605	5.700
Endogenous Time-Invariant				
Distance	0.062**	0.520	0.062**	0.520
LF_ LCC	--	--	0.081*	1.830
JFuel _ LCC	--	--	-0.205	-1.140
Wald χ^2	624.42		625.94	
Number of Groups	21		21	
Observation	2556		2556	

*p-value>0.05

**p-value>0.10

The results show that aircraft size affects flight delays positively. A 10% increase in aircraft size lifts flight delays by 1.9% (see Figure 4.4). Likewise, a 10% increase in the load factor or congestion level of a route leads to a 12.23% increase in flight delays. This result augments earlier research on the positive impact of demand growth, and capacity constraints in flight delays (Dillingham, 2005; Wong et al., 2002). Indeed, the growth in air travelers along with airport capacity constraints leads to more congestion and hence more flight delays.

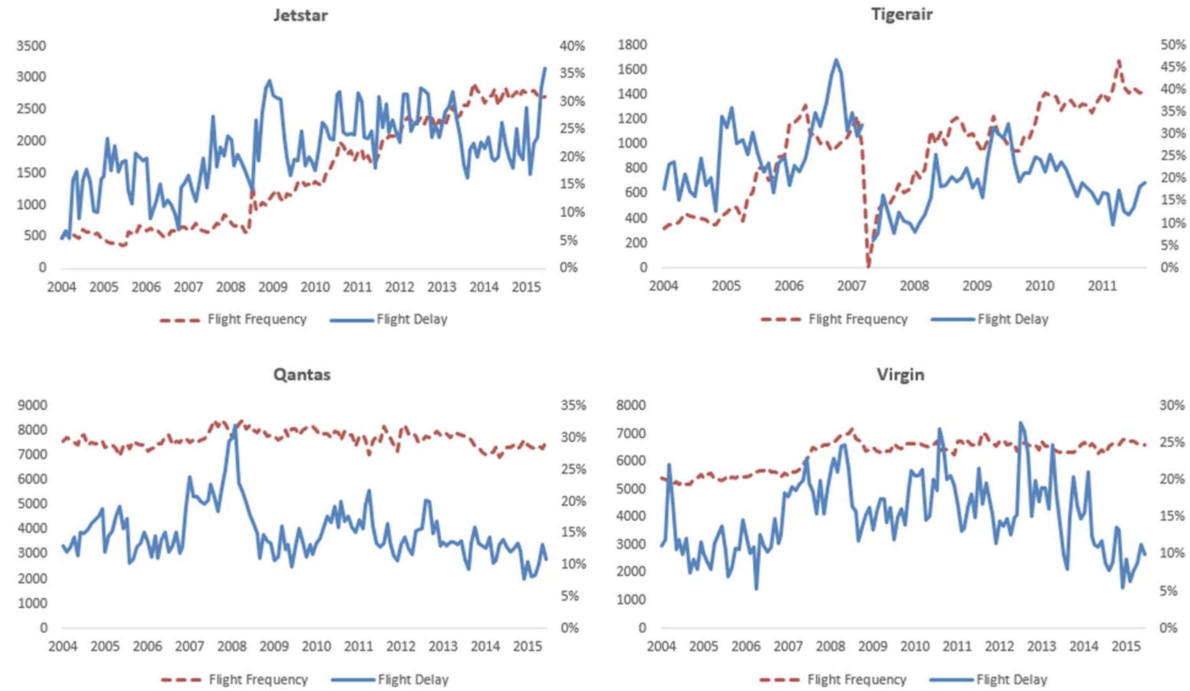

Figure 4.3 Average flight delays against flight frequency[8]

The model results relating to the positive effect of the variables of capacity decisions in flight delays can also be explained by the theory of the economies of density (www.encyclo.co.uk). According to this theory, which is an inherent condition of the supply-demand equilibrium of the aviation industry, more density in terms of greater passenger demand results in more plane-miles by either more flights or larger aircraft size. With no capacity constraints, this nets a lower operating cost per seat, resulting in more passenger demand. However, capacity constraints add flight delays as a new factor to this process. As such, more plane-miles by either more flight frequency or larger aircraft size leads to more flight delays (Zou and Hansen, 2012).

[8] Tigerair flights were grounded briefly by the Civil Aviation Safety Authority of Australia in 2011, due to safety concerns. It only reopened its Melbourne base after returning to the air. Hence, the discontinuity.

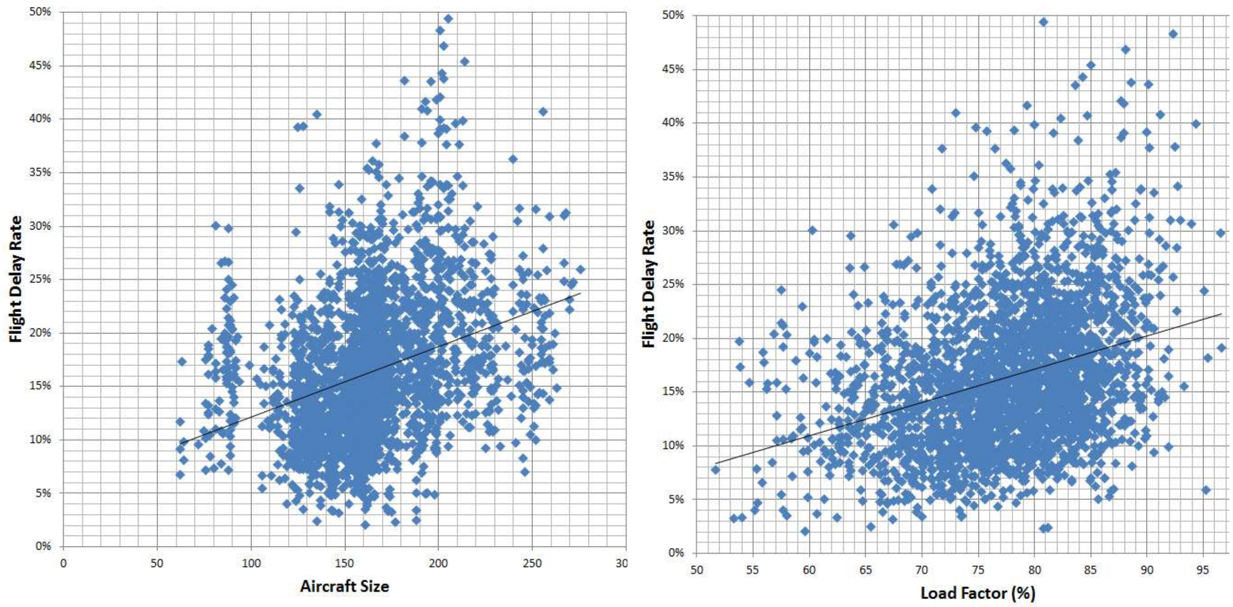

Figure 4.4 Flight delay trend with respect to aircraft size/ load factor growth

The HHI index shows a positive impact on flight delays, suggesting that keener competition between airlines on a route leads to fewer and shorter flight delays. This result confirms the findings of Gillen and Hazledine (2015) about the beneficial effect of competition in flight service improvement. A 10% increase in airline competition reduces flight delays by 1.34%. The variable of low-cost carrier participation rate is applied in modeling to compare the performance of the low-cost carriers against the legacy airlines in mitigating flight delays.

From the model results, the degree and extent of flight delays differ between the low-cost carriers and legacy airlines. The model output suggests that an airline's operating policy is significant to the flight delay model. A higher participation of the low-cost carriers by 10% leads to a higher rate of flight delays, by roughly 6.82% in the mean duration or number of flight delays. For low-cost airlines, as they pursue the low-cost strategy to minimise their operating expenses, the focus of the maintenance programs and traffic systems may be less rigorously observed and conducted compared to those of legacy airlines. As a result, flight delays are more expected for low-cost carriers than legacy airlines due to the higher possibility of delay propagation as well as mechanical faults.

Based on the results, the legacy airlines have been relatively more successful in limiting flight delays than the low-cost carriers, possibly because of their application of more effective traffic systems to predict the initial flight delays and reducing the propagation effect, regular maintenance on their aircrafts to reduce the possibility of mechanical issues, and the access to a hub-and-spoke network to manage air traffic particularly during the peak season.

Likewise, a 10% increase in jet fuel price leads to a 4.79% increase in flight delays. Indeed, airlines apply different capacity algorithms during periods of jet fuel price inflation, which can result in longer and more flight delays. For instance, legacy airlines use larger, more fuel-efficient aircrafts to manage jet fuel inflations (Sibdari et al., 2018), leading to a higher likelihood of flight delays. Figure 4.5 shows the flight delay trend regarding jet fuel price volatility since 2014.

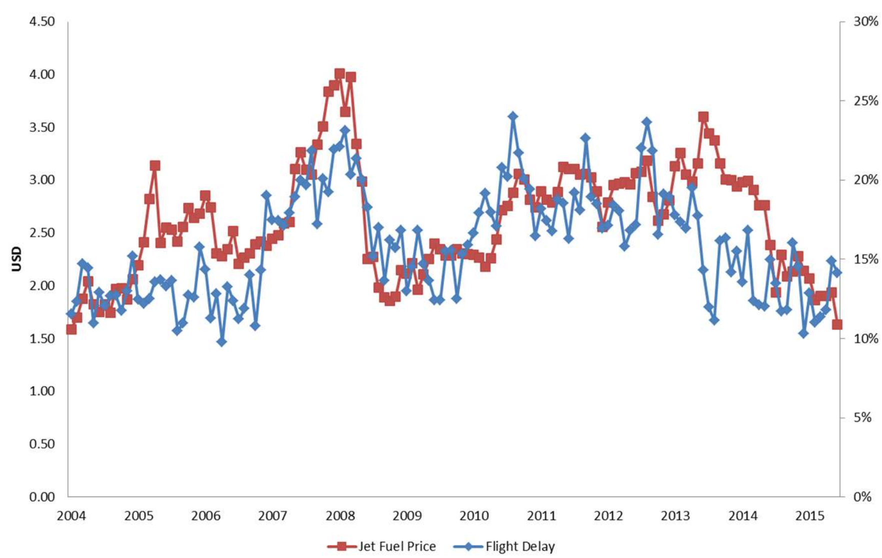

Figure 4.5 Average flight delay trend with respect to jet-fuel price fluctuations

The results show a positive relationship among the socio-economic parameters and flight delays. In fact, population and employment rates are two significant factors in demand modeling that stimulate flight demand. With respect to the route/airline capacity constraints, more demand would lead to a higher density which in turn promotes more flight delays. In contrast, the model estimation indicates a negative relationship between airfare and flight delays. *Ceteris paribus*, a 10% increase in airfare is expected to decrease the likelihood of a flight delay by 2.4%. In fact, higher airfare negatively affects flight demand that leads in lower density. From the estimation model, the variable Distance is statistically insignificant.

4.7.2. Pooled results: Interaction effects

As mentioned in section 4.6.3, Step 2 includes the interaction factors used in the modeling. Table 4.2 presents the results of the Hausman-Taylor regression for Step 2. The coefficients of the main effect factors are similar to those of step 1. As previously described, two interaction factors, LF_ LCC and JFuel_LCC are added to the model to investigate the low-cost carriers' performance on flight delays. From the estimation in step 2, the coefficient of LF_LCC is positive suggesting that a higher level of route congestion has a greater effect on the low-cost carriers compared to the legacy airlines. Legacy airlines have more flexibility in controlling flight delays in highly congested routes, given their access to a range of aircraft types, and the hub and spoke network. Likewise, the results of the jet fuel price interaction variable, JFuel_LCC, are different for the low-cost carriers and legacy airlines. From the model, a higher jet fuel price leads to higher rates of flight delays for the legacy carriers. As one of the key operational principle of low-cost carriers, these airlines usually apply a homogenous fleet of medium-sized aircraft such as the Airbus 320 or Boeing 700/800 leading to less fuel being consumed (Ehmer et al., 2008; Gross and Klemmer, 2014, p. 34). Thus, jet fuel inflation may affect the low-cost carriers less than the legacy airlines.

4.8.Summary

Flight delays are expected to become a widespread and growing phenomenon around the world due to the continued growth in flight demand together with the airline/airport capacity constraints. This study drew some implications which can potentially be applied in explaining flight delays phenomenon in Australia as well as other locations and passenger air-transport markets across the globe where contain both legacy and low-cost carriers as active market players.

This study has identified the airline-related drivers affecting flight delays using a dataset of Australian domestic aviation market. This study highlighted the effect of the variables of capacity decisions in flight delays. On the mechanisms of airlines to mitigate flight delays, strategies in capacity planning can lessen the impact of flight delays. More plane-mile either by more flight frequency or larger aircrafts increase the possibility of flight delays due to the airports' capacity constraints. More flights expect to increase flight delays due to the propagation effect of the initial delay. As such, airlines, could consider reducing the number of flights and size of aircrafts to lessen flight delays. Higher congestion levels lead in more and longer flight delays as indicated by the theory of economies of densities under capacity constraints. Jet fuel inflations enforce airlines to apply different capacity strategies leading in flight delays.

To offset the higher operating expense from the increase in jet fuel price, Australian airlines could adopt different policies in capacity planning and operations that can affect flight delays differently. Interestingly as explored in this study, the low-cost carriers appear to be more successful than the legacy airlines in managing flight delays during periods of jet fuel price inflation. However, these airlines experience weaker performance when controlling flight delays in the highly congested routes. This study suggests that the legacy airlines are more successful in controlling flight delays than the low-cost carriers, as the former has different operating models to apply to lessen the influence of flight delays such as the maintenance programs to reduce mechanical faults or traffic systems to reduce the propagation effects of the initial delays. More attention is required from the policy makers in Australia and elsewhere to encourage their domestic airlines to apply effective traffic systems and approaches to mitigating flight delays. Future research can study the effect of capacity planning of individual routes on flight delays.

Chapter 5

An optimisation model for airlines' capacity decision-making

5.1.Introduction

This chapter is aimed to develop an optimisaiton model of capacity planning to maximise passenger demand of an airline for a given network or airport. The objective function is therefore to identify the best combination of flight frequency and average aircraft size for each route of a given airport (or network) to maximise the total potential passenger demand. Chapters 3 and 4 explored the key determinants of airlines' capacity planning or passenger demand modelling. These findings are applied in this chapter to develop the methodological framework of optimisation model. The rest of this chapter is set as follows; Section 5.2 provides a background on airline capacity planning. In Sections 5.3, the parameters are defined, followed by data description in Section 5.4. Section 5.5 describes the methodological framework of the optimisation model in terms of model specification, proposed technique and model formulation. Section 5.6 presents the econometrical analyses. The optimal solutions of capacity planning are provided in Section 5.7. Section 5.8 concludes.

5.2.Background

Airlines across the globe have experienced economic turmoil such as recessions, de-regulation, and jet fuel fluctuations, forcing them to either merge with other airlines or file for bankruptcy (Baker and Donnet, 2012). There are increasingly fewer options for airlines to respond to such disruptions and uncertainty (Sibdari et al., 2018). As such, airlines are turning to capacity planning to manage their flight demand and operating cost (Carey, 2015; Sibdari et al., 2018).

Capacity planning can affect airlines service quality and operating cost, in turn, altering their profits and market share (Wei and Hansen, 2005). Airlines have applied various aircraft types and different flight schedules on their networks to improve their market share and profitability (Mohammadian et al., 2019a). Capacity planning has become more critical for airlines, compared to the other traditional tools such as revenue management or hedging contracts (Sibdari et al., 2018; Mohammadian et al., 2019a). However, capacity planning is not easy for airlines as they need to consider many factors on both sides of their supply-demand equilibrium and accommodate various limitations such as access to the number and type of aircraft, airports, or even flight regulations. Finding the optimal capacity plan in which an airline can provide the right available seats in right airfares to meet the potential passenger demand, may be challenging as many factors either in supply or demand side would cause an equilibrium shift. This disequilibrium may occur as a result of either a change of micro-level factor, such as bad weather at airport, or macro-level parameter, such as terrorist attacks.

Airlines have historically applied passenger demand forecasts to determine the best combination of flight frequency and type of aircrafts to maximise their profitability or market shares. However, the changes of passenger demand from one month to the following month depend on the changes of different factors such as socio-demographic factors, airfares, and airlines capacity plans. This chapter is aimed to present an optimisation model of airline capacity planning to maximise passenger demand of an airline for a given network or airport. The objective function is therefore to identify the best combination of flight frequency and average aircraft size for each route of a given airport (or network) to maximise the total potential passenger demand.

5.3. Parameters

The four dependent variables of the supply-demand equilibrium used in this study are passenger demand, flight frequency, aircraft size, and flight delay. They are selected to build a system of four non-linear equations. Table 5.1 illustrates the model variables in terms of the definition, data type, and the models where each parameter is targeted to be an explanatory variable. Table 5.1 also list the previous studies where each variable had been used as an explanatory variable in modeling.

Passenger demand (**PASS)** is the most well-recognised variable taken to present the air traffic demand (Jorge-Calderón, 1997; Ito and Lee, 2005; Zhang, 2015; Srisaeng et al., 2015; Binova, 2015). **PASS** is the key factor of airlines' capacity planning and ticket pricing. However, **PASS** is influenced by the quality of airline service (Alamdari and Black, 1992, Pitfield et al., 2010; Zhang, 2015; Srisaeng et al., 2015), and socio-economic and demographic factors (e.g., Jorge-Calderón, 1997, Grosche et al., 2007; Srisaeng et al., 2015; Binova, 2015). The quality of airline service is determined by the factors that comprise flight frequency, aircraft size, airfare, and load factor (Jorge-Calderón, 1997). PASS is sometimes assumed to be inelastic (Teodorovic and Krcmar-Nozic, 1989; Hsu and Wen, 2000; Adler, 2001), or have a bilateral relation to flight frequency and aircraft size, as the key elements of capacity planning (Hsu and Wen, 2003; Pitfield et al., 2010; Mohammadian et al, 2019a). As discussed by Mohammadian et al. (2019a), load factor is known as an insignificant factor in capacity planning in the Australian domestic market, particularly on the medium- and long-haul routes hence it is not considered in this study. Airfare (**Airfare**) is one of the significant variables of PASS. A higher airfare results in a lower level of passenger demand directing airlines to adjust airfares according to the new passenger demand (Zou and Hansen, 2012). The socio-economic factors have been historically applied to estimate PASS (e.g. Jorge-Calderón, 1997; Ito and Lee, 2005). A higher level of the socio-economic factors would increase PASS (Ito and Lee, 2005). Population (**POP**) and employment rate (**EMP**), calculated by the product of the related numbers of the origin-destination (OD) pairs, are applied to reflect the socio-economic factors. Distance affects **PASS** in two ways. While a longer distance would lead in less demand due to the weaker social and business relations between a flight origin and destination, it stimulates passenger demand as it boosts the relative importance of air transportation compared to the other transportation modes (Jorge-Calderón, 1997). According to Mohammadian et al. (2019a), distance influences the airline strategies of capacity planning.

Airlines' capacity decisions are driven by the passenger demand forecasts for different routes. According to Pitfield et al. (2010), a higher **PASS** has more impact on flight frequency rather than aircraft size. The decisions of airlines on the number of flights affect the choice of aircraft and vice versa. The number of departing flights from an airport is applied to estimate flight frequency (**Flight**). Like some earlier studies (e.g. Jorge-Calderón, 1997; Pitfield et al., 2010; Sibdari et al, 2018; Mohammadian et al, 2019a), the average aircraft size (**ASize**) in terms of the average number of available seats per flight is applied in this study. In addition to PASS, other factors such as competition between airlines, jet fuel expenses, and airline policy also would influence airline capacity decisions (Mohammadian et al., 2019a). As discussed by Mohammadian et al. (2019a), while it is expected that the competition between airlines would accompany with more flights and smaller aircraft size, the higher jet fuel costs would result in less flight frequency and larger aircraft. Jet fuel cost (**JetFuel**) has historically been among the highest cost components in airline operating expenses that negatively affects the service quality (e.g., Borenstein and Rose, 2014). Competition would lead to more flights, smaller aircraft size, and more available seats which in turn increases **PASS** (Mohammadian et al., 2019a). The Hirschman–Herfindahl Index (HHI), described in section 3.4, is applied as an indicator of airline competition in the routes examined.

In response to PASS, the low-cost carriers would have different policies on capacity planning compared to the legacy airlines (Mohammadian et al., 2019a). The low-cost carriers (**LCC**) participation in the flight market has been proven to influence quality of flight service that in turn stimulates PASS (Barrett, 2004; Pels et al., 2009; Mohammadian et al., 2019a). **LCC** is estimated by the rate of total number of flights provided by the **LCC** for a given route and period.

Flight delay (**Delay**) is a key facet of service quality, and a performance indicator for air transportation systems. Many factors, at both macro- and micro- levels may influence flight delays (Yu et al., 2019). More **PASS** brings about a higher density which, in turn, results in more Delay potentially (Zou and Hansen, 2012; Yu et al., 2019). In contrast, more Delay leads to less quality airline service which negatively influences **PASS** (Britto et al., 2012). Flight delay is significant in capacity planning because of the interdependency between flight delay and flight frequency (Zou and Hansen, 2012). Principally, flight delays are due to the insufficient supply of air transport services or facilities to meet passenger demand (Abdel-Aty et al., 2007). More flights would reduce the time buffer between flights and inflate the propagation effect which increases the possibility of flight delay (Mohammadian et al., 2019b). Airlines may shift to a smaller number of flights and use larger aircrafts to reduce the flight delay (Zou and Hansen, 2012). However, larger aircraft size also has a higher possibility of being delayed due to more late passengers (Yu et al., 2019). In this study, fight delay (**Delay**) is estimated as the number of departing flights delayed for longer than 15 minutes for a given route and time period. Flight delays are also influenced by seasonality, and weather and climate (e.g. Abdel-Aty et al., 2007). Weather-related variables are known to constitute in 40% of the total delay time (Sun Choi et al., 2016). Bad weather increase aircraft separations which in turn leads in a reduction of airport capacity (Schaefer and Millner, 2001).These factors have been applied in flight delay modeling (Abdel-Aty et al., 2007). We use the variables of average monthly rain (**Rain**), minimum temperature (**LowTemp**)[9], and the season (**Season**) as proxies to identify the weather- and season-induced impacts on flight delays.

[9] Due to the unavailability of monthly data of weather-related determinants of flight delay such as visibility factors or ceiling height factor, **Rain** and **LowTemp** are chosen as the proxies of weather-related factors in this paper.

Table 5.1 List of parameters

Term	Definition	Applicable on Model				Source
		PASS	Flight	ASize	Delay	
Passenger Demand*	Total number of passengers traveled between origin and destination of a given route and month period	×	√	√	√	Pitfield et al., 2010; Sibdari et al, 2018; Mohammadian et al., 2019a
Flight Frequency*	Total number of flights flown between origin and destination of a given route and month period	√	×	√	√	Jorge-Calderón, 1997; Wei and Hansen, 2006; Pels et al., 2009; Pitfield et al., 2010; Mohammadian et al., 2019a
Aircraft Size*	Calculated by total available seats divided by flight frequency between origin and destination of a given route and month period	√	√	×	√	Jorge-Calderón, 1997; Wei and Hansen, 2006; Pitfield et al., 2010; Yu et al., 2019; Mohammadian et al., 2019a
Flight Delay*	Number of flights delayed for longer than 15 mins in departure for a given route and month period	√	√	√	×	Britto et al., 2012; Zou and Hansen, 2012
Airfare*	Australian Domestic Airfare according to Real Best Discount index (ref. month: July 2003) for a given month period	√	×	×	×	Jorge-Calderón, 1997; Wei and Hansen, 2006; Pels et al., 2009; Mohammadian et al., 2019a
Population (billion)**	Computed by multiplying population of each city pair for a given route and month period	√	×	×	×	Jorge-Calderón, 1997; Britto et al., 2012; Mohammadian et al., 2019a
Employment Rate***	Computed by multiplying Employment Rate (%) of each city pair for a given route and month period	√	×	×	×	Ito and Lee, 2005; Mohammadian et al., 2019a
HHI*	Hirschman- Herfindahl Index for a given route and month period	×	√	√	√	Pitfield et al., 2010; Gillen and Hazledine, 2015; Mohammadian et al, 2019a
Jet fuel price****[10]	Average monthly fuel price per gallon in US airline industry (U.S. Gulf Coast kerosene-type jet fuel spot price fob)	×	√	√	√	Ito and Lee, 2005; Sibdari et al, 2018; Mohammadian et al., 2019a

[10] Due to absence of the domestic data of jet fuel cost, the monthly price of the U.S. Gulf Coast kerosene-type jet fuel is applied as a proxy for Jet fuel price.

Term	Definition	Applicable on Model				Source
		PASS	Flight	ASize	Delay	
LCC Participation *	Calculated by dividing total number of flights operated by low cost carriers to total flights for a given route and month period	×	√	√	×	Ito and Lee, 2005; Pels et al., 2009; Mohammadian et al., 2019a
Average Rain_ Origin*****	Average rains recorded in the closest weather station to origin airport for a given route and month period	×	×	×	√	Abdel-Aty et al., 200711;Mehndiratta et al., 2002
Average Rain_ Destination*****	Average rains recorded in the closest weather station to destination airport for a given route and month period	×	×	×	√	Abdel-Aty et al., 2007; Mehndiratta et al., 2002
Temperature_ Origin*****	Minimum of lowest temperatures recorded by the closest weather station to origin airport for a given route and month period	×	×	×	√	Abdel-Aty et al., 2007; Mehndiratta et al., 2002
Temperature_ Destination*****	Minimum of lowest temperatures recorded in the closest weather station to destination airport for a given route and month period	×	×	×	√	Abdel-Aty et al., 2007; Mehndiratta et al., 2002
Season	Dummy variable for Season	×	×	×	√	Abdel-Aty et al., 2007
Distance*	non-stop distance (in kilometers) between airport to airport of origin and destination for a given route	√	√	√	√	Jorge-Calderón, 1997; Pels et al., 2009; Britto et al., 2012; Mohammadian et al, 2019a
Route Dummy	Dummy variable for route *i*	√	√	√	√	Sibdari et al, 2018; Mohammadian et al., 2019a

Data Source: * Department of Infrastructure and Regional Development (DIRD) (http://bitre.gov.au/), ** Australian Bureau of Statistics (ABS) (http://www.abs.gov.au/), *** Department of Employment (http://Imip.gov.au/), *** U.S. EIA (http://www.eia.gov/), ***** BOM, Weather & climate data (http://bom.gov.au/)

[11] Abdel-Aty et al. (2007) used wind speed as the proxy of weather changes.

5.4.Data

To test the proposed optimisation model, the domestic flight data of Melbourne airport for seven routes linking Melbourne to the other state capitals in Australia. Figure 5.1 represents the targeted routes in this study. The dataset includes the O_D monthly data, belonging to all active domestic airlines, from January 2004 to December 2015[12]. Appendix 5.1 summarizes the four dependent variables for each of the given routes. This market is chosen as it provides the required information of the model variables, and all major airlines compete in this market. This model can be extended to other airports and networks.

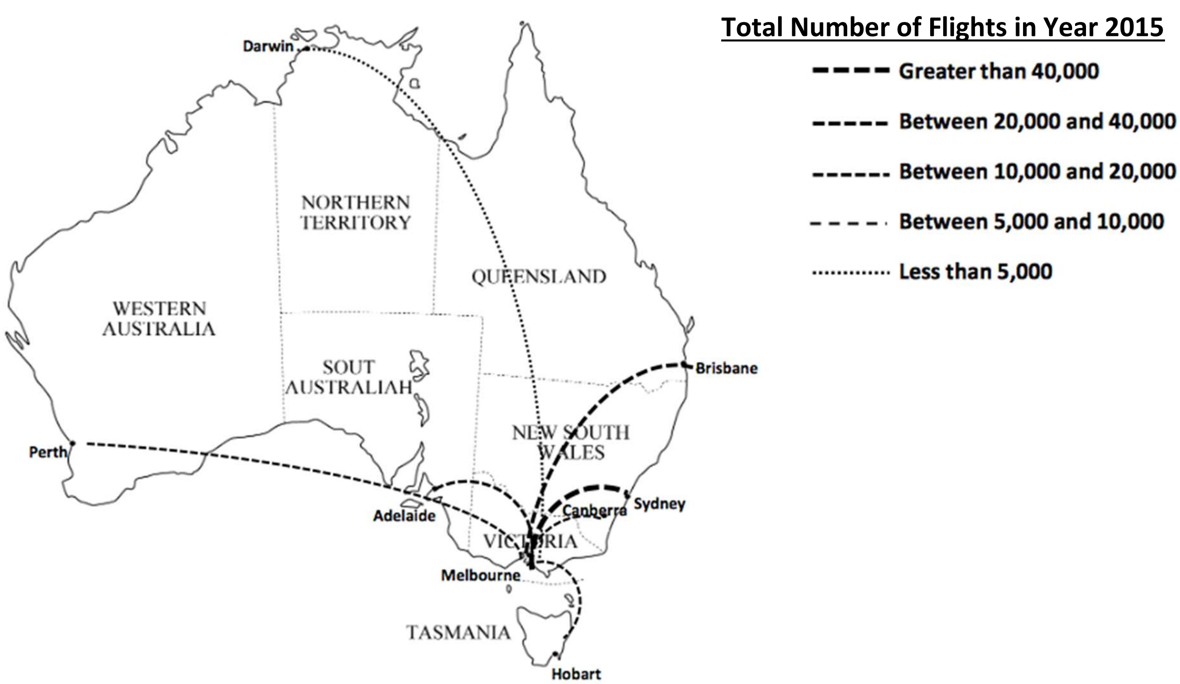

Figure 5.1 Targeted domestic O-D routes (including routes from Melbourne to Adelaide, Hobart, Canberra, Sydney. Brisbane, Perth, and Darwin)

[12] DIRD, Domestic aviation activity reports (http://bitre.gov.au/)

The dataset is built by relying on the data from agencies such as the Department of Infrastructure and Regional Development (DIRD), and the Australian Bureau of Meteorology (BOM). The data of the all parameters, except for flight delay, is seasonally adjusted to explain the industry plan. The flight delay equation comprises the weather- and season-related parameters that potentially offset the seasonal effect of this variable. The data on the average airfare is unavailable for the given market, restricting this driver to as an exogenous factor in the passenger demand modeling.

As the data are categorized as a time-series cross-sectional, the model includes seven route dummy variables. To assess the distance related parameter, using the clustering of Mohammadian et al. (2019), the seven routes under study are categorized into three markets based on route distance: the short-haul market includes the routes between Melbourne and Adelaide, Canberra, Hobart, and Sydney. The medium-haul market only has the Melbourne-Brisbane route. The long-haul markets are the Melbourne-Perth, and Melbourne-Darwin routes.

5.5. Methodological framework

5.5.1. Model Specification

As discussed in Chapters 3 and 4, there are bilateral relations among these four variables; passenger demand, flight frequency, aircraft size, and flight delay, known as endogeneity effect, which cause a causal loop among the variables (Wooldridge, 2013). Figure 5.2 presents the interactions between these variables with the arrows representing causal relationships.

As discussed in Zou and Hansen (2012), any change in capacity would prompt a set of related changes in passenger demand, flight frequency, aircraft size, airfare, and flight delays that would trigger an equilibrium shift. Theoretically, in the aviation industry where the economies of density is an inherent specification of the equilibrium (Zou and Hansen, 2012), in a situation of no congestion, greater density in terms of higher passenger demand leading in more plane-miles obtained through either more number of flights or larger aircrafts. More flights improve the service quality which then leads to greater passenger demand (Else, 1985). Airlines also prefer to operate larger aircraft as they have a lower unit operating cost, and the airlines can offer lower fares. At the same time, cheaper fares stimulate passenger demand leading to higher economic density. Hence, without capacity constraints, there is a virtuous cycle creating higher economic density on the demand side and more plane-miles on the supply side of the flight equilibrium (Zou and Hansen, 2012). However, this notion is no longer valid once the capacity constraint is added to the equilibrium. Capacity constraints add a flight delay factor into the equilibrium. In other words, higher density coupled with the capacity constraints would increase the runway congestion level which results in more flight delays. Flight delays incur extra costs for the airlines, diminishing the economies of density. In fact, higher flight delays lead to less passenger demand either directly or indirectly as an outcome of the airline responses. Airlines need to consider these interactions to make efficient capacity plans for each route on their operating networks. Such a capacity planning helps airlines effectively control operating costs and manage market share.

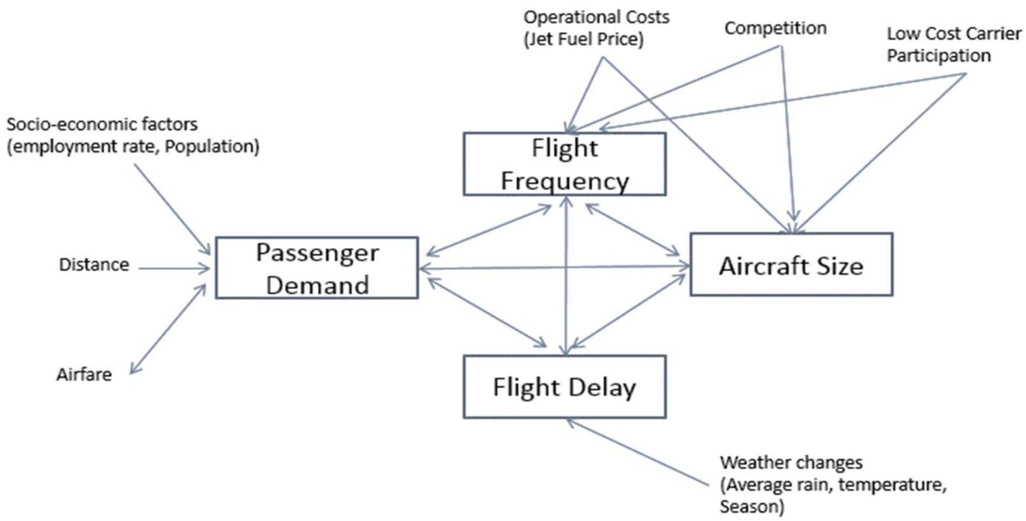

Figure 5.2 Conceptual framework (for reference only; identical to Figure 1.1)

5.5.2. Proposed Technique

In the systems of non-linear equations, a factor change on the supply-demand equilibrium prompts interactions among the variables, making the equilibrium imbalanced, which leads to an equilibrium shift. To estimate the coefficients of the variables, the regression techniques can be applied. However, due to the endogeneity effects among the dependent variables, applying the ordinary least square (OLS) technique potentially leads to biased and inconsistent results (Pitfield et al. ,2010). So, the technique of full system estimators (Baseley, 1988) needs to be applied.

The two popular system estimators are three stage least square method (3SLS) and maximum likelihood estimator (MLE) (or full information maximum likelihood[13]). Under standard conditions, these models are asymptotically equivalent to estimate the structural equations with Normal errors because the two estimators have the same asymptotic distribution (Dhrymes, 1973).

[13] Full information maximum likelihood technically is the same as maximum likelihood estimator when the models are applied on a dataset without missing data. We use maximum likelihood in this study as the applied dataset has no missing observation.

3SLS, in general, is much simpler to compute compared to the MLE especially for a small dataset. These two models are separately applied to deal with endogeneity (Wooldridge, 2013) and to estimate the coefficients of the passenger demand model which is applied in the optimisation model. The results of two techniques are compared in summary sections.

5.5.3. Model formulation

To address the simultaneity in the relationship of the four dependent variables as discussed in Section 5.4.1, a system of four non-linear equations is developed using a series of endogenous and exogenous variables. The aim is to estimate **PASS** which is later used in the optimisation model. The other three equations are included to avoid a possible two-way causation bias. From Section 5.3, a set of exogenous parameters, comprising airfare[14] (**Airfare**), population (**POP**), and employment rate (**EMP**), are applied for each of the four equations.

The optimisation model is aimed to identify the optimal capacity plan of routes of a given airport. Thus, all four equations include dummy variables ($\mathrm{D\_Route_i}$) to analyze the route information which is categorized as time-series cross-sectional data. To avoid multicollinearity between the route dummy variables and distance, distance is removed from the passenger demand equation and is applied to cluster the individual routes. As a result, the optimisation model is applied separately for each cluster to find the optimal solution of the individual routes. The model of Mohammadian et al. (2019)'s is applied to cluster the routes by distance. According to Mohammadian et al. (2019), individual routes are categorized into three markets based on the route distance as follows: short-

[14] The data on the average monthly airfares at the route level is unavailable. The Australian domestic average airfare index is applied instead to reflect this variable. As a result, this study treats airfare as an exogenous parameter for passenger demand.

haul routes with distance shorter than 800 km, medium-haul routes with distance between 800 and 2400 km, and long-haul routes with distance greater than 2400 km.

The factors of Competition (**HHI**), Jet fuel cost (**JetFuel)**, and participation of low-cost carriers (**LCC**) are applied as the explanatory variables of both models of flight frequency (**Flight**) and aircraft size (**ASize**). As endogenous regressors, flight delay (**Delay**) includes the four factors related to the average rain (**Rain)** and low temperature (**LowTemp)** of origin and destination of a given route, season (**Season**) for flight delay modeling.

For each equation, a lagged value of the dependent variable is added as a new predictor, which results in robust estimates of the effects of the explanatory variables, and improves the model fitness (Achen, 2000). Applying this predictor helps us later to identify the optimal changes of flight frequency and aircraft size in period *t* to maximise the passenger demand changes in period *t* compared to those of period *t-1*.

The variables are logarithmic transformed to develop the equations, assuming the relationships among the variables are non-linear (Pitfield et al., 2010). As a result, the coefficient for each parameter reflects the elasticity of the dependent variable with respect to each corresponding parameter in the equation (Ito and Lee, 2005; Wei and Hansen, 2006). The system of four non-linear equations is specified as follows:

$$\log(PASS_{it}) = a_P + a_1\log(PASS_{it-1}) + a_2\log(Flight_{it}) + a_3\log(ASize_{it}) + a_4\log(Delay_{it}) + a_5\log(Pop_{it}) + a_6\log(EMP_{it}) + a_7\log(Airfare_t) + a_{80}\text{D\_Route}_i + \varepsilon_{it1}$$

$$\log(Flight_{it}) = \beta_F + \beta_1\log(Flight_{it-1}) + \beta_2\log(PASS_{it}) + \beta_3\log(ASize_{it}) + \beta_4\log(Delay_{it}) + \beta_5\log(JetFuel_t) + \beta_6\text{LCC}_{it} + \beta_7 HHI_{it} + \beta_8\text{D\_Route}_i + \varepsilon_{it2}$$

$\log(ASize_{it}) = \gamma_A + \gamma_1 \log(ASize_{it-1}) + \gamma_2 \log(PASS_{it}) + \gamma_3 \log(Flight_{it}) +$
$\gamma_4 \log(Delay_{it}) + \gamma_5 \log(JetFuel_t) + \gamma_6 \mathrm{LCC}_{it} + \gamma_7 HHI_{it} + \gamma_8 \mathrm{D\_Route}_i + \varepsilon_{it3}$

$\log(Delay_{it}) = \delta_A + \delta_1 \log(Delay_{it-1}) + \delta_2 \log(PASS_{it}) + \delta_3 \log(Flight_{it}) +$
$\delta_4 \log(ASize_{it}) + \delta_5 \log(Origin\_Rain_{it}) +$
$\delta_6 \log(Dest\_Rain_{it}) + \delta_7 \log(Origin\_LowTemp_{it}) + \delta_8 \log(Dest\_LowTemp_{it}) +$
$\sum_{j=1}^{4} k_j Season_j + \delta_9 \mathrm{D\_Route}_i + \varepsilon_{it4}$

where (all variables for domestic flights)

- $PASS_{it}$: passenger numbers in period *t* for route *i*
- $Flight_{it}$: Flights numbers flown in period *t* for route *i*
- $Asize_{it}$: Average aircraft size in period *t* for route *i*
- $Delay_{it}$: Number of flights delayed in departure in period *t* for route *i*
- $Airfare_t$: Domestic airfare index in period t
- POP_{it}: Products of populations of origin-destination states in period *t* for route *i*
- EMP_{it}: Products of employment rate of origin-destination states in period *t* for route *i*
- $JetFuel_t$: Average jet fuel price per gallon in period *t*
- HHI_{it}: HHI in period *t* for route *i*
- LCC_{it}: Participation rate of low-cost carriers in period *t* for route *i*
- $Origin\_Rain_{it}$: Average rainfall of origin city in period *t* for route *i*
- $Dest\_Rain_{it}$: Average rainfall of destination city in period *t* for route *i*
- $Origin\_LowTemp_{it}$: Minimum temperature of origin city in period *t* for route *i*
- $Dest\_LowTemp_{it}$: Minimum temperature of destination city in period *t* for route *i*
- $Season_j$: Dummy variable for Season *j (j:1 to 4)*
- $\mathrm{D\_Route}_i$: Dummy variable for route *i.*

As previously indicated, the coefficients of the air passenger model are applied in the next step to develop the objective function of the optimisation model.

The optimisation model presents as per below; The objective is to maximise the total passenger demand $PASS_t$ of a given network in period *t* found as a sum of individual passenger demand of all routes *i*=1, 2, …, *n* included in a given network/airport. Flight frequency $(Flight_{it})$ and aircraft size $ASize_{it}$ are decision variables in the model which are found separately for each route of a given network/airport with respect to the route and network/airport constraints. The values of the other parameters are fixed, and found from the dataset for a given period *t*, and route *i.*

Objective: $Max\ PASS_t = \sum_{i=1}^{n} PASS_{it}$ i[15]=1, 2…. n

with

$\log(PASS_{it}) = a_P +$
$a_1 \log(PASS_{it-1}) + a_2 \log(Flight_{it}) + a_3 \log(ASize_{it}) + a_4 \log(Delay_{it}) + a_5 \log(Pop_{it}) +$
$a_6 \log(EMP_{it}) + a_7 \log(Airfare_t) + a_8 \text{D\_Route}_i + \varepsilon_{it1}$

Subject to:

Route constraints:

$a_i < Flight_{it} < b_i\ where\ a_i$is min F_i and b_i is max F_i in the period under study

$c_i < ASize_{it} < d_i\ where\ C_i$is min $ASize_i$ and d_i is max $ASize_i$ in the period under study

Network/Airport constraints:

$\sum_{i=1}^{n} Flight_{it} < F$ where *F* is the network/airport constraint on Flight departure for all given routes in the period *t*

$\sum_{i=1}^{n} Flight_{it} * ASize_{it} < S$ where *S* is the network/airport constraint on the total available seats in the period *t*

[15] Route Code is applied as i in the case study.

The two sets of constraints are defined to develop the optimisation model. The route constraint identifies the possible range of flight frequency (*a*, *b*), and aircraft size (*c*, *d*) for each route i=1, 2…, *n* of a given network/airport with respect to the historical data. This constraint is initiated to avoid any impractical solution from being generated by the optimisation model.

Airlines have a limited access to the number and types of aircraft. Given by this statement is applicable for an operating network/ airport, therefore the constraint of flight frequency is defined as the total available flights (*F*) that can be assigned to the all routes of a given network/ airport. This constraint is calculated as the total flights reported for all routes of a given network/ airport in period *t.* This total number reflects the total actual flights flown by airlines, not their nominal flight capacities. However, we apply this number to perform a fair assessment on actual passenger demand reported by airlines compared to potential passenger demand estimated by the optimal capacity decisions. Due to the unavailability of the aircraft type data, the total available seats *S* is applied to control for the aircraft size allocation of the optimal solution to the routes under study. In short, the total seats of the optimal solution, found from multiplying the optimal flight frequency and average aircraft size, must not be greater than actual total seats of the given network/ airport or airport in period *t*.

As indicated in Section 5.4.2, two techniques; three stage least square method (3SLS), and maximum likelihood estimator (MLE) are applied separately to estimate the objective function of passenger demand and develop the optimisation model.

5.6. Econometric analysis

5.6.1. Econometrical Analysis: Three-Stage Least Square method

The three-stage least square method (3SLS), as an instrumental variables estimator, combine Seemingly Unrelated Regression (SUR), as a system equation, with two-stage least squares estimation (2SLS) (Amemiya, 1977). The 3SLS technique allows the correlations of the unobserved disturbances among all equations, as well as restrictions across coefficients of various equations. By considering such correlations among the equations, it improves the efficiency of equation-by-equation estimation. The 3SLS technique estimates all coefficients of model equations simultaneously unlike the single equation estimators such as 2SLS that separately estimates the coefficients of each equation.

As mentioned, there are four endogenous variables (**PASS**, **Flight**, **ASize**, and **Delay**) in the system of non-linear equations. The other variables, comprising the lagged endogenous variables such as the lagged passenger demand $PASS_{it-1}$, and lagged flight frequency $Flight_{it-1}$ are exogenous. For each equation, there is a set of instruments. For **PASS** equation, **POP**, **EMP** and **Airfare** are applied as instruments. **JetFuel**, **LCC** and **HHI** play this role for both equations of Flight and **Asize**. For **Delay**, the factors of **Rain**, **LowTemp** and **Season** are used as instruments.

Table 5.2 and Appendices 5.2, 5.3, and 5.4 summarizes the econometric results of the 3SLS technique for each dependent variable on the dataset of Melbourne airport. The results are presented by distance groups and are targeted to apply separately for the optimisation in the next step. The primary interest of this econometric analysis is to estimate the coefficients of the air passenger demand model as it is applied in the next step to develop the optimisation model. From the estimation, more flights lead to greater demand, albeit to different degrees in the distance markets. Passenger demand has the highest elasticity to flight frequency in the medium-haul, followed by the short-haul routes. This coefficient is statistically insignificant in the long-haul market. Similar to flight frequency, more passenger demand is expected by larger aircraft size for the short and long-haul markets. The coefficient of aircraft size is statistically insignificant in the medium-haul market. The coefficients of the other parameters in the demand model concur with earlier studies. From the results, the passenger demand is more elastic to the changes of flight frequency compared to aircraft size in the all three markets. Higher airfares lead to less passenger demand in all distance groups. Population and employment rate both positively affect air passenger demand. Appendix 5.5 presents a summary of the results of 3SLS analysis for the three distance groups. From the R^2 outputs, the coefficients of the air passenger demand equation can used to develop the optimisation function.

Table 5.2 3SLS Outputs for Passenger Demand equation

	Short-Haul		Medium-Haul		Long-Haul	
Variables	Coef.	P-value	Coef.	P-value	Coef.	P-value
Passenger Demand						
Flight	0.145	0.000	0.387	0.001	0.004	0.954
ASize	0.059	0.069	-0.361	0.391	0.238	0.014
Delay	-0.020	0.044	0.000	0.986	0.103	0.001
Lag_Pass	0.596	0.000	0.334	0.000	0.687	0.000
Airfare	-0.106	0.000	-0.111	0.120	-0.284	0.018
Population	0.089	0.001	0.201	0.125	0.142	0.090
Employment Rate	0.249	0.006	0.487	0.007	0.916	0.000
<u>Route (Route Code)</u>						
Melboune_Adelaide (1312)						
Melbourne_Hobart (1316)	-0.604	0.000	0.000		0.686	0.060
Melbourne_Canberra (1317)	-0.822	0.000				
Melboune_Sydney (1319)	0.861	0.000				
Melbourne_Brisbane (1318)			0.000			
Melbourne_Perth (1314)						
Melbourne_Darwin (1315)					0.686	0.060
Constant	-0.174	0.675	0.186	0.921	-0.349	0.877

5.6.2. Econometrical Analysis: Maximum likelihood estimation (MLE)

Maximum likelihood estimation is a forecasting technique that applies a set of given observations to estimate the parameters of a model with the objective of maximizing the likelihood function. The method of maximum likelihood is applicable with an extensive variety of statistical analyses (Blatt and Hero, 2007). Assuming a parameter is normally distributed with an unknown mean and variance, these two elements can be estimated with MLE through a sample set of a population. Given the normal model, MLE takes the mean and variance as parameters and estimate parametric values of these two elements by making the observed results the most probable (Veall, 1990). To perform the MLE analysis for the proposed model, the structural equation modeling (SEM) feature is applied in STATA software. Applying MLE, SEM assumes the full joint normality of all endogenous and exogenous variables. The MEL estimation by SEM is a simple approach to estimate the sophisticated model of this study. The model outputs are targeted to apply to develop the optimisation approach. The MEL estimation can be applied as comparative model to verify the results of 3SLS technique.

Appendix 5.6 graphically illustrates the model that developed in SEM and analysed by MLE in STATA. The list of parameters and their relations in terms of one-way or bilateral are exactly developed based on the framework of proposed model described in section 3, making it feasible to apply the MLE outputs as a comparative model to verify the 3SLS results. Table 5.3 summarizes the MLE results on the Melbourne airport dataset. As can be seen, the coefficients of parameters are different across the seven routes under study which is one of the advantages of MLE compared to 3SLS. However, as previously described, the complexity of MLE modeling on SEM may result in some unobserved biased estimation. Appendix 5.7 provides the outputs of overall goodness of fits. High LR test of the model versus the saturated model indicates the estimation ineffective, which it was predictable regarding the size and complexity of the proposed model. However, as can be seen in Appendix 5.8, reported the Equation-level goodness of fit, the R-squared of the MLE estimation of the routes is relatively high (higher than 90%), making it possible to apply the estimated passenger demand model as the objective function of the optimisation model.

To compare the outputs of 3SLS with MLE, the total mean square error (MSE) is calculated for the both techniques on the Melbourne airport dataset. The results indicated the MSE of 9,390,316 for MLE technique compared to that of 13,700,000 for 3SLS. Based on MSE index, MLE seems to be relatively a better forecasting technique of passenger demand model compared to 3SLS. However, the coefficients of the 3SLS estimation are more consistent, and supported by the findings of the prior studies (e.g. Mohammadian et al., 2019). Compared to the 3SLS, the greater number of coefficients of MLE model is statistically insignificant which may cause the optimisation results impractical at the final step.

Table 5.3 MLE Outputs

Equation	Route						
	1312	1314	1315	1316	1317	1318	1319
Passenger							
Flight	0.24	0.22	0.04*	0.19	0.07*	0.27	0.29
ASize	0.17	0.28	0.46	0.17*	-0.06*	-0.21*	0.20*
Delay	0.00*	0.03*	0.09	-0.07	0.01*	0.00*	0.00*
Lag-Pass	0.53	0.56	0.65	0.60	0.77	0.48	0.44
Airfare	-0.08	-0.01*	0.11*	0.00*	-0.03*	-0.02*	-0.03
Population	0.20	0.11*	-0.02*	0.59	0.05*	0.21	0.20
Employment Rate	0.75	0.60	1.56	0.32	0.17*	0.34	0.21
Constant	-3.86	-2.82	-5.46	-7.43	-0.26*	-1.66	-1.83*
Flight							
Pass	0.04*	0.15	-0.10	-0.11*	-0.12*	-0.14	0.33
Asize	0.15	0.04	0.23	0.20	0.23	0.42	-0.39
Delay	0.01	-0.04	0.03*	0.00*	-0.02*	0.02*	0.01*
Lag_Flight	0.60	0.49	0.78	0.78	0.80	0.57	0.38
LC Participation rate	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Equation	Route						
	1312	1314	1315	1316	1317	1318	1319
HHI	-0.03*	-0.02*	-0.26	-0.05*	0.02	-0.08	-0.10
Jet Fuel	0.01	0.04	0.25	0.07	0.08	-0.01	0.02
Constant	0.58	0.53	0.23*	0.50*	0.55*	1.00	1.09
Aircraft Size							
Pass	-0.14	0.03*	0.00*	0.02*	-0.06	0.15	-0.63
Flight	0.16	0.19	-0.35	0.03	0.11	0.02	0.49
Delay	0.00*	-0.01*	0.33*	0.00*	-0.02*	-0.01	0.02
Lag_Asize	0.82	0.80	1.11	0.86	0.82	0.63	0.78
LC Participation rate	0.00	0.00	0.00*	0.00*	0.00*	0.00	0.00
HHI	-0.03	0.00	-0.07	0.00*	-0.02	0.00	0.09
Jet Fuel	0.01	0.00	0.04*	-0.01*	0.02*	0.02	-0.03
Constant	0.64	-0.13*	0.07*	0.16*	0.41	0.02	2.29
Flight Delay							
Pass	-0.84	0.50*	0.11	-0.39	-0.84	-0.59	3.56
Flight	1.45	-0.23*	0.78	1.27	2.21	0.41	-2.30
Asize	-0.69	-0.05*	-0.61	1.75	-2.00	3.34	-0.87
Lag_Delay	0.55	0.63	0.07*	0.42	0.24	0.61	0.59
Origin_Rain	0.03*	0.01*	0.00*	0.05	0.10	0.05	0.05
Dest_Rain	0.02	0.03	0.01*	0.01*	-0.04	0.03*	-0.01
Orign_Temperature	0.03	-0.02	-0.02	0.01	0.08*	-0.02	0.03
Dest_Temperature	0.00	-0.01	-0.01	-0.01*	-0.06*	0.00	-0.05
Season	0.00*	0.00*	0.00*	0.00	0.00*	0.00	0.00
Constant	2.31*	-1.03*	0.44*	-4.30	3.59	-4.81	-9.08

* Insignificant at confidence level of 0.1

5.7.Optimization

5.7.1. Optimization: Three-Stage Least Square method

As mentioned, the objective of the optimisation model is to identify the best combination of flight frequency $Flight_i$, and aircraft size $ASize_i$ for the set routes of Melbourne airport to maximise the total passenger demand (*PASS*). The data of December 2015 are applied to estimate the constant part of the model. Based on the data of December 2015, the total number of flights (F) and total available seats (S) in the given routes are 5,386, and 925,827 respectively. Lingo ver. 18.0 is used to solve the model. Table 5.4 presents the output of the optimisation model and provides a comparison between the estimated passenger demand of the optimal solution and the actuals based on the data of airline activities as reported.

Objective

$Max\ (PASS) = 10^{0.145\log(Fligh\ _{1312})+\ 0.059log(ASize_{1312})+\ 4.467} +$
$10^{0.145\log(Fli\ \ \ _{1316})+\ 0.059log(ASize_{1316})+\ 4.306} + 10^{0.145\log(Fli\ \ \ _{1317})+\ 0.059log(ASize_{1317})+\ 4.134} +$
$10^{0.145\log(Fligh\ _{1319})+\ 0.059log(ASize_{1319})+\ 4.952} + 10^{0.387\log(Flig\ \ _{1318})-0.361log(ASize_{1318})+\ 4.792} +$
$10^{0.004\log(Fligh\ _{1315})+\ 0.238log(ASize_{1315})+\ 3.603} + 10^{0.004\log(Flight_{1314})+0.238log(ASize_{1314})+\ 4.400}$

s.t.

Airport Constraints

Flight frequency:

$Flight_{1312}+Flight_{1316}+Flight_{1317}+Flight_{1319}+Flight_{1318}+Flight_{1315}+Flight_{1314} \leq 5386;$

Aircraft size:

$Flight_{1312} * ASize_{1312}+Flight_{1316} * ASize_{1316}+Flight_{1317} * ASize_{1317} +\ Flight_{1319}{}^{*}ASize_{1319} +$
$Flight_{1318} * ASize_{1318}+Flight_{1315} * ASize_{1315}+Flight_{1314} * ASize_{1314} \leq 925827;$

Route Constraints

Route 1312: $546 <= Flight_{1312} <= 774$; $138 <= ASize_{1312} <= 164$
Route 1318: $669 <= Flight_{1318} <= 1096$; $148 <= ASize_{1318} <= 169$
Route 1317: $242 <= Flight_{1317} <= 516$; $106 <= ASize_{1317} <= 142$
Route 1315: $24 <= Flight_{1315} <= 100$; $103 <= ASize_{1315} <= 195$
Route 1316: $264 <= Flight_{1316} <= 489$; $130 <= ASize_{1316} <= 173$
Route 1314: $265 <= Flight_{1314} <= 564$; $178 <= ASize_{1314} <= 232$
Route 1319: $1309 <= Flight_{1319} <= 2417$; $173 <= ASize_{1319} <= 199$

Table 5.4 shows how a change in the capacity planning of the routes may excite passenger demand and maximise the overall demand of a given network or airport. The optimal solution increases the total potential demand of the given routes by 1.72%. This increase can potentially result in a substantial effect on an airline profits because, with no requirement of capacity expansion, adding a passenger to a flight has almost zero marginal cost for an airline. From the optimal solution, more flights with smaller aircrafts would lead to greater passenger demand. The model allocated less flight frequency and smaller aircrafts to the Melbourne-Adelaide leg, causing a drop of 0.56% in passenger demand. The optimal solution suggests that an increase in both the elements of capacity planning for the Melbourne-Sydney leg, lifts the potential passenger demand by 1.7%. The optimal solution suggests more flights with smaller aircrafts for the other two short-haul routes. For the Melbourne-Brisbane route, more flights using smaller planes should lift passenger demand. On the long-haul market, the airlines may manage their market share with fewer flights but larger planes.

Table 5.4 Optimisation model outputs vs. actual data (for Melbourne Airport, Dec 2015)- 3SLS Model

			Actual			**Model Estimation**			**Change**		
Route Name	**Route Code**	**Route Type**	Flight	ASize	PASS	Flight	ASize	PASS	Flight	ASize	PASS
Melboune_Adelaide	1312	Short-Haul	751	155	102,500	744	144	101,921	-0.93%	-7.10%	-0.56%
Melbourne_Hobart	1316	Short-Haul	436	164	65,573	489	134	65,885	12.16%	-18.29%	0.48%
Melbourne_Canberra	1317	Short-Haul	300	128	41,817	321	123	42,130	7.00%	-3.91%	0.75%
Melboune_Sydney	1319	Short-Haul	2,250	178	370,147	2,417	199	376,446	7.42%	11.80%	1.70%
Melbourne_Brisbane	1318	Medium-Haul	1,090	166	146,683	1,096	148	153,216	0.55%	-10.84%	4.45%
Melbourne_Perth	1314	Long-Haul	471	218	92,448	265	232	93,611	-43.74%	6.42%	1.26%
Melbourne_Darwin	1315	Long-Haul	88	175	13,924	24	195	14,213	-72.73%	11.43%	2.08%
Total			**5,386**		**833,092**	**5,356**		**847,423**	**-0.56%**		**1.72%**

5.7.2. Optimisation Model: Maximum likelihood estimation (MLE)

With respect to the outputs of MLE analysis at the section 5.6.2, the objective function of optimisation algorithm is as below. The constraints are the same as 3SLS model indicated in section 5.7.1. The coefficients of the variables are different in the all seven routes in MLE function compared to those of 3SLS which only were different between distance groups.

Objective function:

Max (P)=10^(0.238log($Flight_{1312}$)+ 0.169log($ASize_{1312}$)+ 3.943)+10^(0.191log($Flight_{1316}$)+ 0.167log($ASize_{1316}$)+ 3.926)+10^(0.071log($Flight_{1317}$)- 0.055log($ASize_{1317}$)+ 4.558)+10^(0.291log($Flight_{1319}$)+ 0.196log($ASize_{1319}$)+ 4.143)+10^(0.273Log($Flight_{1318}$)- 0.209log($ASize_{1318}$)+ 4.796)+10^(0.037log($Flight_{1315}$)+ 0.456log($ASize_{1315}$)+ 3.021)+10^(0.216log($Flight_{1314}$)+ 0.278log($ASize_{1314}$)+ 3.717);

s.t.

Airport Constraints

Flight frequency:

$Flight_{1312}+Flight_{1316}+Flight_{1317}+Flight_{1319}+Flight_{1318}+Flight_{1315}+Flight_{1314} \leq 5386$;

Aircraft size:

$Flight_{1312} * ASize_{1312}+Flight_{1316} * ASize_{1316}+Flight_{1317} * ASize_{1317} + Flight_{1319} * ASize_{1319} + Flight_{1318} * ASize_{1318}+Flight_{1315} * ASize_{1315}+Flight_{1314} * ASize_{1314} \leq 925827$;

Route Constraints

Route 1312: $546 <= Flight_{1312} <= 774$; $138 <= ASize_{1312} <= 164$
Route 1318: $669 <= Flight_{1318} <= 1096$; $148 <= ASize_{1318} <= 169$
Route 1317: $242 <= Flight_{1317} <= 516$; $106 <= ASize_{1317} <= 142$
Route 1315: $24 <= Flight_{1315} <= 100$; $103 <= ASize_{1315} <= 195$
Route 1316: $264 <= Flight_{1316} <= 489$; $130 <= ASize_{1316} <= 173$
Route 1314: $265 <= Flight_{1314} <= 564$; $178 <= ASize_{1314} <= 232$
Route 1319: $1309 <= Flight_{1319} <= 2417$; $173 <= ASize_{1319} <= 199$

Table 5.5 presents the results of optimisation model based on the MEL econometric outputs. The optimal solution provided by MEL model indicates an increase of 0.66% in the total potential passenger demand compared to the actual capacity plan of the given routes. As can be seen on table 5.5, with respect to the optimal solution of MEL model, the passenger demand of four routes expect to increase in the expense of the other three routes including Melbourne-Hobart, Melbourne-Canberra, and Melbourne-Brisbane. In more details, the optimal solution suggests that an increase in both flight frequency and aircraft size for the legs of Melbourne-Adelaide and Melbourne-Sydney. By contrast, the optimal solution allocates less seats to the other two short-haul route, Melbourne-Hobart and Melbourne-Canberra, causing a passenger demand decreases of 3.56% and 0.49% on these legs respectively. Likewise, the model allocates less flight frequency and smaller aircrafts to the Melbourne-Brisbane leg, causing a drop of 10.37% in passenger demand. On the long-haul market, the optimal solution causes an increase in passenger demand, albeit with different strategy of capacity planning. MLE solution utilizes 96.30% of the capacity of available flights, relatively less than the utilization rate of 3SLS optimal solution, 99.44%.

Table 5.5 Optimisation model outputs vs actual data (for Melbourne Airport, Dec 2015)-MLE Model

			Actual			Model Estimation			Change		
Route Name	**Route Code**	**Route Type**	Flight	ASize	Pass	Flight	ASize	Pass	Flight	ASize	Pass
Melboune_Adelaide	1312	Short-Haul	751	155	100,015	774	164	101,703	3.06%	5.81%	1.69%
Melbourne_Hobart	1316	Short-Haul	436	164	63,326	442	130	61,069	1.38%	-20.73%	-3.56%
Melbourne_Canberra	1317	Short-Haul	300	128	41,583	242	106	41,378	-19.33%	-17.19%	-0.49%
Melboune_Sydney	1319	Short-Haul	2,250	178	366,310	2,417	199	382,336	7.42%	11.80%	4.38%
Melbourne_Brisbane	1318	Medium-Haul	1,090	166	145,098	669	148	130,059	-38.62%	-10.84%	-10.37%
Melbourne_Perth	1314	Long-Haul	471	218	88,665	564	232	93,805	19.75%	6.42%	5.80%
Melbourne_Darwin	1315	Long-Haul	88	175	13,159	25	195	13,184	-71.59%	11.43%	0.19%
Total			**5,386**		**818,155**	**5,133**		**823,534**	**-4.70%**		**0.66%**

Compared to 3SLS solution, MLE solution totally applied only 5,133 flights, and benefited less from the available flights (5,386), compared to the total assigned flights of 5,356 in the 3SLS solution. However, as mentioned in section 5.6.2, some of the coefficients in MLE estimation are statistically insignificant which cause some ambiguity around the validity of its results.

5.8.Summary

Capacity planning is an approach employed by airlines to manage their market share and operating costs. The flight frequency and aircraft size are identified to be key drivers in the supply-demand equilibrium. Airlines make their capacity decisions through demand forecasting. However, this study shows that any capacity decision later influences the other drivers of the supply-demand equilibrium, causing an equilibrium shift. As gaining a higher market share is key in the aviation industry, this study has attempted to develop a complete capacity planning model with respect to the key drivers of the flight route market. The purpose is to identify the elasticity of passenger demand to the two elements of capacity planning for different markets. This study finds that the strategies of capacity planning may influence passenger demand differently for different markets. Therefore, the airport infrastructure investors and developers also must consider the effects of flight frequency and aircraft size on passenger demand, in addition to the other factors of supply-demand equilibrium to decide on the capacity development projects of airports or networks, especially when airport expansion are infrequent.

A series of exogenous and endogenous factors identified from Chapter 3 and 4 to initiate the air supply-demand equilibrium. Through a system of four non-linear equations based on the economies of density theory, a comprehensive model comprising all key drivers of supply-demand equilibrium was developed. Due to the two-way relations among the four dependent variables, 3SLS and MLE were applied separately for the econometric analysis of the data of Melbourne airport, as a case study. In the optimisation section, different constraints were stated to make the final solution practical. Based on the econometric results of two models, MLE had a less calculated MSE compared to that of 3SLS. However, the estimation of 3SLS was known more practical and statistically meaningful. The econometric outputs of two models were applied to develop the objective function of optimisation algorithm. In the optimisation section, different constraints were defined to make the final solution practical. The optimal solution developed on the 3SLS results, was identified as a better solution with a 1.72% improvement on the potential passenger demand of the given routes of the Melbourne airport compare to a 0.66% for MLE model. The proposed model can thus be applied to assist governments and investors in decision making and prioritization of the capacity development of the airports or networks. Applying a longer time series data to develop the dataset helps to better and more practical estimation in the econometric analysis. While this paper addressed airlines' capacity by flight frequency and aircraft size, the research can be improved by considering the actual types of aircrafts flown on the routes. Due to the data limitation, airfare was only applied as an exogenous parameter in the passenger demand equation. The number of departing flights delayed was used as the proxy for the flight delay variable. However, including the other proxies such as flight delays in minutes potentially improves the results of the flight delay equation. Applying the cost-related factors can improve capacity planning under supply-demand equilibrium. For this, more investigation is needed.

The proposed model of this study can effectively be applied to assist for decision makings of the capacity development of the airports or networks. The application of longer time series data to develop the dataset helps for the better and more practical estimation in the econometric analysis section. Due to the complexity of the supply-demand equilibrium, the further investigation is required for any possible improvement on the model.

The next chapter presents the key research findings and revisit the predetermined research questions.

Chapter 6

Conclusion and Future Research

6.1.Introduction

This chapter presents general conclusions and key findings derived from the modelling in the prior chapters. This study developed a novel optimisation model of the airlines' capacity planning under supply-demand equilibrium of the flight market. The econometrical analyses in the previous chapters also revealed many findings related to the key determinants of passenger demand modelling as well as airlines' capacity planning. The following sections discuss how the research questions, indicated in this thesis, are answered and assesses the implication of the thesis. Section 6.2 highlights the key findings, followed by section 6.3 which discusses how the research questions are answered in this thesis. Section 6.4 presents the contribution of the study, followed by assessing the implication of thesis in section 6.5. Section 6.6 discusses the key research limitations and opportunities for future research. In the final section, the chapter is summarised to provide the final comments on the key findings.

6.2. Research summary

This thesis developed an optimisation model for airline capacity planning under the supply-demand equilibrium of flight market. The model aims to find the best combination of flight frequency and aircraft size in the individual routes to maximise the total potential passenger demand for a given airport or hub-and-spoke network. The model framework was developed based on the theory of economies of density and included all key drivers of capacity planning on both sides of the equilibrium. The significance of the model's variables and parameters and their interactions were tested and verified by implementing innovative econometrical analyses on the domestic flight market of Australia in Chapter 3 and 4, and an optimisation model was developed in Chapter 5.

Chapter 3 was targeted to identify the key drivers of airline's capacity decisions under the supply-demand equilibrium. Regarding the endogeneity effect among passenger demand and the variables of capacity planning, the two-stage least square technique was applied on the time-series cross-sectional data of 21 major routes in the Australian domestic market. To further explore the airlines' policies of capacity planning, the routes were categorised into three markets, short-, medium-, and long-haul markets. The bilateral relations among passenger demand and the variables of capacity decisions were verified by the Durbin-Wu-Hausman test, and the consistency of the instrumental variables was tested by the weak instrument test, as suggested by Stock et al. (2002). The econometrical analysis confirmed the relationship of passenger demand and the variables of capacity planning as well as identified the significant supply- and demand-side parameters which required us to consider the supply-demand equilibrium of the flight market.

Chapter 4 presented the empirical analyses to identify the impact of the variable of capacity planning on flight delay. According to the economies of density, given the capacity constraints, more plane-miles in terms of more flight frequency and aircraft size leads to flight delay that offsets the positive impact of higher densities on the generalised cost of customers and in turn passenger demand. Therefore, this step was targeted to statistically test the interaction among flight delay and the variables of capacity planning by applying the Hausman–Taylor regression estimator technique. This technique effectively addressed the endogeneity among the model's variables as well as the time-invariant parameters in modelling. By adding other airline-related factors and introducing the interaction variables, this explored the impact of airlines' policy and performance on flight delay.

According to the supply-demand framework, initiated according to the economies of density, and finalised based on the results of econometrical analyses in Chapter 3 and 4, a system of four non-linear equations, passenger demand, flight frequency, aircraft size, and load factor, was developed in Chapter 4. This system comprehensively comprised all endogenous and exogenous variables on both sides of the supply-demand equilibrium. As the system included the simultaneous equations, two full system statistical techniques, 3SLS and MLE, were separately applied to estimate the empirical model. The data of routes, linking Melbourne to the other capitals in the Australian domestic market, was applied to test the model. The estimated passenger demand equation was applied as the objective function of the optimisation model at the final step. A series of capacity constraints at the route and airport level was introduced to lead the optimisation outputs to practical results. The optimisation model was separately applied for 3SLS and MLE estimations and their results were compared. This model provides the optimal solutions of capacity planning at the route level to maximise the total potential demand for a given airport or network. The proposed model can thus be applied to assist governments and investors in decision making and prioritisation of the capacity development of the airports or networks.

Next section discusses the research findings in detail.

6.3. Key Research Findings

This section succinctly provides the key findings derived from the literature review and thesis modelling. The findings are discussed for each of the prior chapters in the following sub-sections.

6.3.1. Literature review

Chapter 2 provided a literature review on the key drivers and modelling of airline's capacity planning, passenger demand, flight delay, and air supply-demand equilibrium. With respect to the literature review provided in chapter 2, this section provides a summary of the findings and research problems.

- The prior research omitted how the domestic airlines managed and met the demands of the potential passengers of the regional routes and transformed this demand into capacity algorithms. None of the previous studies explored the drivers of the supply-demand equilibrium on the level of the origin-destination routes and the factors that influence the capacity planning in the Australian domestic market.
- No study has comprehensively addressed the subject of airline capacity planning in the Australian domestic market. Similar studies in the literature primarily focused on domestic or international flight routes of the other regions across the world.
- The empirical studies have yet to examine the factors affecting the phenomenon of flight delay in Australia. Most prior studies employed a micro level analysis involving daily data to examine the factors that influence flight delays and there is a lack of research that applies new route- and Australian domestic-level factors to model flight delays.
- The prior studies mostly applied pure theoretical approaches to develop the optimisation model of capacity planning and there is a lack of empirical studies in the modelling.
- The prior studies have applied an airline's profitability or operating cost as the model objective to determine the optimal number of flights under supply-demand equilibrium. None of the previous studies applied flight demand as the objective, and flight frequency and aircraft size as the decision variables.
- The prior studies of capacity planning mostly used aggregate micro-level data. Therefore, there is a lack of studies which apply macro-level factors in the modelling.

6.3.2. Identification of Key Drivers of Airlines' Capacity Decisions

This step, discussed in chapter 3, was aimed to identify the antecedents of the airlines' capacity decisions. The associated research question of the step was "*RQ1: What are the key determinants* *of airlines' capacity decisions under the supply-demand equilibrium of flight market?*". This step examined the factors on both sides of the supply-demand equilibrium using monthly data of 21 major domestic routes linking 8 major cities between January 2004 and December 2015. The dataset contained the historical data of four dominant airlines, Jetstar, Tiger Airways, Qantas, and Virgin Australia, and other active airlines in the Australian domestic flight market.

To investigate the relationship between flight demand and the variables of capacity decisions (flight frequency, aircraft size, load factor, and available seats), the pooled series cross-sectional data were analysed using a two-stage least-squares method to model the supply-demand interaction. Durbin-Wu-Hausman (DWH) test, as suggested by Davidson and MacKinnon (1993), was applied to verify the endogeneity between passenger demand and the variables of capacity decisions. Weak instrument test, as suggested by Stock et al. (2002), was applied to ensure that the instrumental variable estimates were consistent. The key findings of this step were as below:

- Airlines applied different strategies of capacity planning for short-, medium-, and long-haul markets. These policies differently influence passenger demand.
- In the short-haul market, airlines were more flexible in the choice of aircraft. Therefore, aircraft size was relatively more significant than flight frequency in the passenger demand model for the short-haul market. By contrast, fight frequency was identified as the key driver of capacity planning for the medium- and long-haul routes.
- Passenger demand inflations led to more flights with the same or even smaller sized aircrafts in the medium-haul market. Both flight frequency and aircraft size were significant in capacity planning in the long-haul market, albeit with less elasticity of aircraft size on passenger demand than that of the short-haul market.

- The results suggested that a higher demand for flights primarily results in increased flight frequency rather than increased aircraft size or load factor, which was consistent with the literature (Pitfield et al., 2010).
- The number of flights and airline's choice of aircraft size influenced passenger demand. Load factor was recognised as an insignificant factor in the passenger demand model. The effect of socio-economic factors, i.e. population and employment rate, on passengers was relatively significant in the long-haul routes.
- Contrary to the findings of Ito and Lee (2005) in which jet fuel cost was found to be an insignificant factor in the airline demand model, this factor was shown to be a driver on both sides of the supply-demand equilibrium of Australia's domestic market. However, this factor differently influenced passenger demand on short-, medium-, and long-haul routes.
- On the short-haul routes, the increase in oil price and related products stimulated flight demand and resulted in an increase in flight frequency at the expense of demand reduction in surface transportation.
- Jet-fuel price inflations resulted in greater passenger demand for the routes with higher levels of industrial specifications.
- Competition among the airlines enhanced flight demand and resulted in more flights, smaller aircraft size, and lower load factors, which together reflect higher service quality in the domestic flight market in Australia.
- Low-cost carriers stimulated flight demand, increased flight frequency, reduced aircraft size and load factor, and enhanced the available flight capacity in the short-haul market.
- The higher jet fuel prices scaled up aircraft size on all O-D routes in the market.

- Differentiated airline strategies were adopted for capacity decisions between the short-haul and long-haul routes.
- Competition and low-cost carriers stimulated flight demand, improve quality of service, and increase the total number of available seats.
- Contrary to earlier studies, this research found that on short-haul routes, higher jet fuel costs result in greater flight demand and more flights.
- Socio-economic parameters, population, and participation rates affected flight demand more strongly on long-haul routes than on short-haul routes.

6.3.3. Impact of Airlines' Capacity Decisions on Flight Delay

This step, considered in chapter 4, investigated the antecedents of flight delays and how airline operations, particularly airline capacity planning, contribute to such an important issue in the aviation industry. The associated research question was "RQ*2: How does an airline's capacity decision influence flight delays?*". The public domain data of the airlines in Australia's domestic aviation market was applied to develop the model. This data included monthly data of 21 major domestic routes linking 8 major cities from January 2004 to December 2015 and is taken from the four dominant airlines, Jetstar, Tiger Airways, Qantas, and Virgin Australia, and other active airlines in the Australian domestic flight market.

Due to the endogeneity among the variables as well as the existence of time-invariant variables in modelling, the Hausman-Taylor regression method was applied to estimate the econometric model. The key findings of this chapter were as follows:

- The estimations indicated the variables of airlines' capacity decisions (flight frequency, aircraft size, passenger load factor) as significant determinants of flight delays.
- Interestingly, the findings of this study showed a negative relation between flight frequency and flight delay.
- Load factor was identified as a significant factor affecting flight delay.
- Keen competition between airlines was recognised to improve the air service quality in the case of less flight delay.
- The increase in airlines' operating expenses in terms of jet fuel cost inflation was identified as a key driver in flight delay.
- Higher jet fuel costs were identified to lead to higher rates of flight delay for Qantas and Virgin, as legacy carriers, than for Jetstar and Tigerair as low-cost carriers.
- Legacy carriers were relatively more successful in controlling flight delay than low-cost carriers

6.3.4. Optimisation Model for Airlines' Capacity Decision-making

This step, discussed in chapter 5, developed a model to optimise the capacity planning of Australia's airlines under supply-demand equilibrium and improve airline fleet planning and airport infrastructure development. The research question addressed by this step was "*RQ3: How can airline capacity decisions be optimised for the individual routes of a given market to maximise the total potential flight demand with respect to the market's capacity constraints?*". The objective was to find the best combination of flight frequency and aircraft size for the individual routes relative to an airport so as to maximise the total passenger demand with respect to the routes and airport capacity constraints. Exogenous and endogenous factors were identified to initiate the air supply-demand equilibrium. The supply-demand equilibrium was outlined based on a system of four non-linear equations involving passenger demand, flight frequency, aircraft size, and flight delay. On the bi-relations among the dependent variables, the two full system models, three-stage least square (3SLS) and maximum likelihood estimation (MLE) were applied to build the model. To test the model, the data of seven Australian domestic routes, linking Melbourne to the other major cities in Australia, were used to estimate the model parameters. A non-linear optimisation model was applied to find the optimal solutions. The key findings were as below:

- The results indicated how optimum airlines capacity decisions can improve the potential flight demand.
- The results proposed a new capacity model for the airlines with respect to all key drivers under the air supply-demand equilibrium.
- The optimal solution of 3SLS indicates a 1.72% increase in the potential demand of departure flights for the given routes of Melbourne airport compared to the actual plan of the domestic airlines for the same period (Dec 2015), compared to that of MEL which presents a 0.66% increase in the potential demand of departure flights.
- The results showed the elasticity of passenger demand with respect to flight frequency and aircraft size are different in different markets

6.4. Meeting the research Objectives

This thesis aimed to develop an optimisation model for airlines' capacity planning under the supply-demand equilibrium of the flight market. To achieve this, this thesis set three main objectives and implemented them accordingly in three executive steps: (1) Identification of key drivers on airlines' capacity decisions, (2) identification of the impact of airlines' capacity decisions on flight delay, and (3) optimisation model for airlines' capacity decision-making. The research objectives were developed in compliance of the research questions indicated in Section

1.2 of chapter 1. The main objectives of the first two steps were to identify the key drivers of the supply-demand equilibrium and their interactions in order to developing a comprehensive framework for modelling in step 3. Step 3 was exclusively aimed to develop an optimisation model for airlines' capacity planning under the supply-demand equilibrium of the flight market.

Chapter 3 addressed the first objective and answered the three predetermined questions:

(1) *Are the airlines' capacity strategies different for short- and long-haul routes? If so, what factors drive these strategies?*

To answer this question, the routes under study were clustered, in Section 3.6.1.2, into three distance groups of short-, medium-, and long-hauls as proposed by Abrahams (1983). According to the data specification, the econometrical technique of two-stage least square method was applied separately to these three markets, and the results were compared in Section 3.7.

(2) How do the supply side parameters, including competition, participation of low-cost carriers, and jet fuel cost inflation, affect passenger demand?

The airline-related factors including competition between airlines, participation of low-cost carriers, and jet fuel price were described in section 3.4. Hirschman–Herfindahl Index (HHI) was introduced as a proxy to address competition between airlines. All these three parameters were applied for modelling in section 3.6.3. The outputs of econometrical analysis of these three factors besides the other airline-related and -non-related factors are discussed in Section 3.7.

(3) How do the demand-related factors influence the airlines' capacity decisions?

This thesis initially identified passenger demand as the demand-related factor to assess the impact of demand-related factors on the airlines' capacity decision. However, because of the endogeneity effect between passenger demand and the variables of capacity planning, discussed in Section 3.6.1.3, three instrumental variables, population, employment rate, and airfare, were added as new factors to the demand side of the equilibrium to offset the endogeneity effect. Applying these factors was the first step of the TSLS modelling in Section 3.6.3 and resulted in the findings on the impact of demand-related factors in the airlines' capacity decisions in Section 3.7.

By answering all above questions, Chapter 3 successfully addressed and achieved the first objective of this thesis.

As discussed in Chapter 1, more plane-miles either by more flight frequency or larger aircraft leads to higher rates of flight delay due to capacity constraints. That was the reason why the second objective of this thesis was to identify the impact of airlines' capacity decisions on flight delay. Chapter 4 exclusively addressed the second objective by successfully addressing the questions below:

(1) How do airline-related factors affect flight delay?

Airline-related factors including the variables of capacity planning, flight frequency, aircraft size, and load factor were identified in section 4.4. The flight delay model was developed based on Hausman and Taylor's instrumental variable estimator in section 4.6. To identify the impact of airline-related factors, the Australian domestic data on the flight market was applied and the findings were explored in section 4.7

(2) How does flight delay rate vary between airlines?

To explore the impact of airlines' performance on flight delay, the factor of low-cost carrier (LCC) participation as well as interaction variables were added to the study in section 4.4. Section 4.7.1 explored the findings about the impact of airlines' policy, in terms of low-cost carrier and legacy airlines, on flight delay. Section 4.7.2 also provided findings on the variables' interaction effects related to the performance of low-cost carriers compared to the legacy airlines to manage flight delays in the case of jet fuel price inflation as well as high congestion of routes.

By addressing the above questions, Chapter 4 effectively achieved the second objective of this thesis. The findings of Chapter 3 and 4 were effectively applied to form the conceptual framework of the supply-demand equilibrium of the flight market which was later used to initiate the optimisation model in Chapter 5.

Chapter 5 addressed the last objective which is related to the development of an optimisation model for airlines' capacity decision-making under the supply-demand equilibrium. The key question was *how does the change in the airline's capacity decision stimulate passenger demand?*

To address this question, an optimisation model was developed by applying the variables of capacity decision, flight frequency, and aircraft size as decision variables and passenger demand as the objective function. A system of four non-linear equations was developed to create the objective function in section 5.5. This function was applied in a non-linear optimisation model in section 5.5.3 as a solution to reveal how the changes in an airline's capacity decision can trigger passenger demand. To answer the key question of Chapter 5, the proposed optimisation model was developed separately based on 3SLS and MLE techniques in section 5.7 and applied using the data on Melbourne airport. The findings of the optimisation model in sections 5.7 and 5.8 successfully addressed the key question of Chapter 5.

By successfully addressing the all key questions, the main purpose of this thesis, to develop an optimisation model for airline capacity planning under supply-demand equilibrium of the flight market, was therefore achieved.

6.5.Contribution of the study

The overall contribution of this study was the development of an innovative optimisation model for airline capacity planning under the supply-demand equilibrium of the flight market. This study consisted of three steps with the following key contributions:

Step 1: Identification of key drivers on airlines' capacity decisions

This step developed an econometrical model by the application of the TSLS technique to identify the key drivers of airline's capacity planning and analyse their relationship under the supply-demand equilibrium of the Australian domestic flight market. A series of endogenous and exogenous variables, from the both sides of air supply-demand equilibrium, were novelty applied to develop the econometric model. This model considered the endogeneity effect between passenger demand and the variables of capacity planning. It was also implemented in different distance markets to highlight different strategies of airlines' capacity planning.

Step 2: Identification of the impact of airlines' capacity decisions on flight delay

This step developed an econometric model by using the Hausman–Taylor regression estimator to identify the impact of airline capacity planning on flight delay. This model included airline- and non-airline-related factors in modelling and introduced the interaction factors to reveal airlines' performance in controlling flight delay. By applying this model, this step identified how airlines' capacity decisions could influence flight delay and how low-cost carriers relatively control flight delay in the case of jet fuel price inflations as well as of airport congestion as compared to the legacy airlines.

Step 3: Optimisation model for airlines' capacity decision-making

An innovative optimisation model was developed for airline's capacity planning under supply-demand equilibrium of the flight market. This model was based on the theory of economies of density and applied the time-series cross-sectional data of flight market under a system of four non-linear equations to empirically estimate the coefficients of passenger demand equation as the objective function. This model comprehensively included all key drivers on both sides of the equilibrium and considers the bilateral relations among the key variables: passenger demand, flight frequency, aircraft size, and flight delay. The techniques of 3SLS and MLE were applied and tested by using the data of routes related to the Melbourne airport. This study novelty considered flight demand as the objective and flight frequency and aircraft size as the decision variables. The macro- and micro-level factors were effectively applied together in the modelling. A series of innovative constraints were introduced in the level of airport and routes to practically control the amount of decision variables.

6.6. Planning Implications

Capacity planning is one of the significant tools that airlines apply to manage passenger demand and control air traffic. Airlines may change the number of flights, apply different types of aircrafts, upgrade the seats in the aircraft, or even increase the load factor. This process is significant as it helps airlines maintain their market shares and manage their operating costs. The relative importance of capacity planning has been increasing due to the diminishing significance of other tools such as airfare management or hedging contracts. However, capacity planning is sophisticated for airlines as they need to consider many criteria and their interactions for such decision-making.

This study proposed a new optimisation model for capacity planning which considers all key drivers of the supply-demand equilibrium of the flight market. Compared to other models of capacity planning that generally contain a relatively a short list of micro-level factors in modelling, the proposed model contains all required macro- and micro-level factors. The proposed model considers all key socio-demographic as well as airline-related factors to determine the optimal capacity decisions. It simultaneously considers the specification of the origin and destination such as population and employment rate as well as of airline-related factors such as competition between airlines, participation of low-cost carriers, and jet fuel inflations to identify the optimal capacity decisions of a given route. As the proposed model applies flight frequency and aircraft size for such decision-making, airlines can determine the elasticity of passenger demand to these two variables separately and differentiate their strategies of capacity planning across different markets.

The proposed model can be effectively applied to assist airlines in capacity planning of an airport or a hub-and-spoke network with respect to all capacity constraints at the level of route as well as airport or network. Therefore, it helps airlines to make the right decisions in terms of increasing the number of flights or aircraft size for the individual routes to maximise the total potential passenger demand for a given airport or network.

The proposed model can potentially be used to assist governments and policy makers in decision making and prioritization of the capacity development of the airports or networks. It determines the elasticity of passenger demand to the different factors on both sides of supply-demand equilibrium. By having the forecasts of model's factors, the model may identify the capacity constraints of airports and networks to meet the potential passenger demand, and in turn determine the investment priorities of airport or network infrastructure developments.

6.7. Limitations and Future Research

There are a few limitations in this study that are related to the research scope as well as the applied dataset. These limitations are mainly related to the data access of a few factors such as airfare and jet fuel price, which were applied within the different steps to either identify the key drivers of the supply-demand equilibrium or develop the optimisation model. These limitations and their related potential future research are separately outlined below:

Using the theory of full equilibrium to develop the optimisation model

As discussed in section 1.3, this study applied the theory of partial equilibrium as a base for optimisation model development. Therefore, the factors of supply-demand equilibrium of the flight market were analysed independently from prices and quantities of transportation substitutions such as vehicles and trains. Without having the factors of the other transportation modes in modelling, it was sometimes challenging to sufficiently interpret the relationship among the factors. Particularly in short-haul routes where surface transportation is a potential substitution of air transport, the quantities and prices of all modes of transportation need to be considered to provide a holistic picture of key drivers of capacity planning and their interactions under supply-demand equilibriums of the transportation market. Therefore, this study suggests applying the theory of full equilibrium, which comprises the factors of the other transportation modes, to extend the proposed model of this study.

Investigating the impact of oil price inflation and of its related products on air and surface transportation

Due to the unavailability of the jet fuel cost information in the Australian domestic market, this study used the monthly information of the U.S. Gulf Coast Kerosene-Type Jet Fuel Spot Price to address this parameter in the proposed model. This limitation decreased the preciseness of the outputs of statistical analyses relating to the relationship between jet fuel price with the other variables of air supply-demand equilibrium.

Further research is required to investigate the impact of oil price inflation and its related products on air and surface transportation. For example, as discussed in section 3.7, jet fuel inflation leads to increased passenger demand in the short-haul market. This positive effect seems to correlate with the price of oil products and their effects on flight and surface transportation in short-haul markets where competing modes of transportation are available for passengers. To fully analyse this effect, the data on other transportation modes needs to be added to the model. Therefore, airline capacity planning with a full picture of the supply-demand equilibrium of all modes of transportation could be pursued in future research.

Using airfare data in the route level

Due to the data limitation, airfare was only applied as an exogenous parameter in the passenger demand equation of the optimisation model in Chapter 5. Because of the absence of monthly data on average airfare at the route level, the best discount index of Australian domestic airfare was applied as a proxy for airfare. As this index only provides the average airfare in the domestic market, this study diminished the significance of this factor in modelling and considered airfare as an exogenous factor in the passenger demand model. Therefore, this study suggests applying the data of other flight markets, with the average airfare at the route level, in future research. As a result, the significance of airfare can potentially be upgraded to become a key variable of airline capacity planning under the supply-demand equilibrium.

Using airline-level data in modelling

This study investigated the key drivers of capacity planning and developed an optimisation model at the route level. The data of four dominant airlines, Qantas, Virgin, Jetstar, and Tigerair, and the other active airlines were consolidated to provide the required dataset. However, this study can be expanded by adding the airline dimension in modelling. In future research, the data of individual airlines can be applied separately at the route level. With the airline dimension in modelling, further explorations can be done on the airline's policies and performance of capacity planning in different markets.

Using flight delay in minutes for modelling

As a research limitation, the number of departing flights delayed was used as the proxy for the flight delay variable in both econometrical models in Chapter 4 and optimisation model in Chapter 5. With respect to the statistical output, this study suggests applying other proxies such as flight delay in minutes that potentially improves the results of the flight delay equations.

Applying the optimisation model to other airports and hub-and-spoke networks across the globe

The data of the seven routes linking Melbourne airport to the other capitals was applied to test the optimisation model. As discussed in section 2.4, the Australian domestic flight market is geographically and economically different from that of other regions such as the US or Europe. Therefore, the application of a proposed optimisation model to other airports and hub-and-spoke networks surely leads to further explorations about the airlines' policies and capacity planning as well as the elasticity of passenger demand to airline- and non-airline-related factors on both sides of the supply-demand equilibrium.

Flight delay modelling based on daily data

Chapter 4 presented an econometrical model to identify the antecedents of flight delay based on the aggregate monthly data of the Australian domestic market. The aim was also to determine how airline's capacity decisions influence flight delay. This study suggests the application of the econometrical model, proposed in chapter 4, to the other highly congested routes where there is access to daily data.

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Appendix 2.1 Literature Review on Flight Delay

Author	Region	Market		Target		Taxonomy					Method				Research Objective	Technique
		Domestic	International	Airport	Airline	Flight Delay Forecasting	Delay Propagation	Delay as parameter	Reduction of Delay impact	Delay impact	Statistical Analysis	Operation Research	Machine Learning	Meta-Heuristic		
Wieland (1997)	USA	×				×									Delay Prediction	Detailed Policy Assessment Tool
Reynolds-F. and Button (1999)	Europe	×		×				×			×				Examination of the current capacity of the EU's airport infrastructure	Quantitative analysis
Hansen (2002)	USA	×		×						×					Runway delay externalities	Queuing model
Wu and Caves (2002)	Europe				×				×			×			Scheduling of aircraft rotation by balancing the use of schedule time	Non-linear Optimisation model
Abdelghanya et al. (2004)	USA	×										×			A projection of flight delays and alerts for possible future breaks during irregular operation conditions	Classical shortest path algorithm
Wu (2005)	Europe				×		×								Inherent delays of airline schedules resulting from limited buffer times and stochastic disruptions in airline operations	Simulation model
Abdel-Aty et al. (2007)	USA	×				×					×				Periodic patterns of arrival delay	Statistical two-stage approach
Hunter et al. (2007)	USA	×		×					×			×			Traffic flow management evaluation platform	Simulation
AhmadBeygi et al. (2008)	USA	×					×								Relationship between the scheduling of aircraft and the operational performance	Quantitative Analysis
Madas and Zografos (2008)	Europe	×		×				×				×			Multi-criteria evaluation and selection of the most compatible slot allocation strategy	AHP Technique
Soomer and Franx (2008)	Europe	×		×					×					×	Collaborative decision making to provide cost functions related to arrival delays	Problem-specific local search heuristic
Tu et al. (2008)	USA					×					×			×	Estimating flight departure delay distributions	Nonparametric methods

Author	Region	Market		Target		Taxonomy					Method				Research Objective	Technique
		Domestic	International	Airport	Airline	Flight Delay Forecasting	Delay Propagation	Delay as parameter	Reduction of Delay impact	Delay impact	Statistical Analysis	Operation Research	Machine Learning	Meta-Heuristic		
Zonglei et al. (2009)	Asia			×		×	×						×		Forecasting flight delays	Content-based recommendation system
Pai (2010)	USA	×			×			×			×				Determinants of aircraft size and frequency of flights	Statistical analysis
Dück et al. (2012)	USA		×				×		×		×				Improving the stability of aircraft routes and crew pairings	Heuristic iterative approach
Wong and Tsai (2012)	Asia				×		×								Flight delay propagation	The Cox proportional hazards model
Cao and Fang (2012)	USA								×					×	Flight departure delays analysis	Genetic algorithm
Britto et al. (2012)	USA	×			×			×			×				The impact of flight delays on both passenger demand and airfares	Econometrical Analysis
Zou and Hansen (2012)	USA	×			×			×			×				Delay-reduction benefits from aviation infrastructure investment under competitive supply-demand equilibrium	Aggregate, statistical cost estimation approach
Ferrer et al. (2012)	USA		×							×					Effects of flight delays on passengers' future purchasing behavior	Econometrical Analysis
Lubbe and Victor (2012)	South Africa									×	×				Cost of flight delays to corporations	Quantitative Analysis
Pyrgiotis et al. (2013)	USA	×		×			×					×			Delay Forecasting	Approximate Network Delays (AND) model
Xiong and Hansen (2013)	USA				×	×					×				US domestic airlines' cancellation decision-making	Revealed preference approach
SUN et al. (2013)	Asia		×	×		×					×				Relation of flight delay and air traffic movements	Analytical model
Peterson et al. (2013)	USA	×								×					Economic costs of delayed flights	USAGE model
Hao et al. (2014)	USA	×		×						×	×				Impact of the three New York airports on delay	AFAA SWAC simulation model

Author	Region	Market		Target		Taxonomy					Method				Research Objective	Technique
		Domestic	International	Airport	Airline	Flight Delay Forecasting	Delay Propagation	Delay as parameter	Reduction of Delay impact	Delay impact	Statistical Analysis	Operation Research	Machine Learning	Meta-Heuristic		
Vlachos and Lin (2014)	Asia	×						×			×				Key factors that determine business traveler loyalty	Hierarchical regression analysis
Zou and Hansen (2014)	USA	×			×			×			×				Flight delay impact on airfare and flight frequency	Econometrical Analysis
Baumgarten et al. (2014)	USA			×		×					×				Relationship between hubbing activities and flight delays	Multi-period unobserved effects model
Kafle and Zou (2016)	USA	×					×				×				Delay propagation patterns	Joint discrete-continuous econometric model

Appendix 3.1 Hausman test on the demand model

```
                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |     fixed        random       Difference          S.E.
-------------+----------------------------------------------------------------
Low_Cost_c~r |    .0197099     .0041248        .0155852               .
Log_SA_Jet~l |   -.0048177     .0036581       -.0084758               .
      HHI_SA |   -.0940098    -.3885579        .2945481               .
log_Produc~e |    1.274551     .4514845        .8230664               .
Log_SA_air~n |   -.0246256    -.1968088        .1721832               .
     Log_POP |     .468463     .6460965       -.1776335         .0491544
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =      159.48
                Prob>chi2 =      0.0000
                (V_b-V_B is not positive definite)
```

Appendix 3.2 Descriptive statistics for variables in the short-haul routes (N = 782)

Variable	Mean	Std. dev.	Min	Max
Flight Frequency	1930.73	1207.64	559.00	5301.00
Average Aircraft Size	150.01	31.70	62.08	199.13
Load Factor (%)	76.801	7.219	51.700	91.100
Number of Available Seats	310267	242986	65920	925812
Number of Passengers	243838	201091	42232	768124
Jet Fuel Price	2.604	0.532	1.490	4.120
Number of Low-Cost Carriers	0.906	0.882	0.000	2.000
HHI	0.395	0.075	0.272	0.801
Employment Rate	5246	269	4649	5903
Airfare	128.26	23.702	98.34	165.50
Population (in billion)	15,000	15,200	1,620	46,000

Appendix 3.3 Descriptive statistics for variables in the medium-haul routes (N = 1,025)

Variable	Mean	Std. dev.	Min	Max
Flight Frequency	650.19	563.17	80.00	2288.00
Average Aircraft Size	150.88	14.10	114.82	179.14
Load Factor (%)	77.73	6.20	55.30	92.60
Number of Available Seats	100,827	92,973	12,528	380,086
Number of Passengers	79,609	74,993	10,547	312,669
Jet Fuel Price	2.61	0.53	1.49	4.12
Number of Low-Cost Carriers	0.73	0.69	0.00	2.00
HHI	0.44	0.09	0.29	0.78
Employment Rate	5,286	303	4,655	6,089
Airfare	127.85	22.72	98.34	165.50
Population (in billion)	7,070	7,480	503	28,800

Appendix 3.4 Descriptive statistics for variables in the long-haul routes (N = 803)

Variable	Mean	Std. dev.	Min	Max
Flight Frequency	413.66	301.73	64.00	1,197.00
Average Aircraft Size	195.73	32.68	102.71	276.49
Load Factor (%)	79.13	7.37	53.30	96.60
Number of Available Seats	86,818	69,291	8,051	260,884
Number of Passengers	69,650	55,731	5,694	201,143
Jet Fuel Price	2.62	0.52	1.49	4.12
Number of Low-Cost Carriers	0.70	0.75	0.00	2.00
HHI	0.46	0.10	0.26	1.00
Employment Rate	5,384	198	4,678	5,839
Airfare	130.46	23.29	98.34	165.50
Population (in billion)	7,190	6,380	508	20,000

Appendix 3.5 Weak instrument test

First-stage regression summary statistics

Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(3,2607)	Prob > F
Log_SA_Pas~r	0.9907	0.9906	0.4170	621.582	0.0000

Minimum eigenvalue statistic = 621.583

Critical Values # of endogenous regressors: 1
Ho: Instruments are weak # of excluded instruments: 3

	5%	10%	20%	30%
2SLS relative bias	13.91	9.08	6.46	5.39
	10%	15%	20%	25%
2SLS Size of nominal 5% Wald test	22.30	12.83	9.54	7.80
LIML Size of nominal 5% Wald test	6.46	4.36	3.69	3.32

Appendix 3.6 The coefficients of the Routes' Dummy variable

Route Dummy	PASS		FF		ASIZE		LF		SEATS	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Short-Haul Routes										
D_AdlMel	-0.25	-7.82	-0.32	-9.06	0.16	5.90	0.15	5.54	-0.15	-5.57
D_BneSyd	-0.20	-34.90	-0.13	-8.96	0.07	5.91	0.06	5.38	-0.06	-5.43
D_CbrSyd	-0.34	-5.94	-0.18	-3.39	0.03	0.68	0.15	3.60	-0.15	-3.65
D_CbrMel	-0.29	-4.59	-0.40	-7.60	0.21	5.00	0.19	4.59	-0.19	-4.62
D_HbrMel	-0.25	-4.38	-0.55	-10.57	0.31	7.57	0.23	5.75	-0.23	-5.79
D_MelSyd	Omitted									
Medium-Haul Routes										
D_AdlBne	0.01	0.97	0.07	8.43	-0.03	-3.88	-0.04	-6.97	0.05	7.14
D_AdlCbr	-0.19	-5.79	-0.01	-0.79	-0.04	-2.60	0.06	4.04	-0.05	-3.90
D_AdlSyd	0.34	16.36	0.22	8.00	-0.06	-2.57	-0.17	-8.01	0.17	8.04
D_AdlPer	0.04	6.59	0.10	13.77	-0.06	-10.67	-0.04	-6.83	0.04	7.06
D_BneCbr	0.15	8.67	0.17	19.67	-0.09	-12.92	-0.08	-12.50	0.08	12.65
D_BneHbr	-0.41	-39.50	-0.14	-5.68	0.01	0.65	0.13	7.16	-0.12	-7.06
D_BneMel	0.47	14.20	0.31	7.43	-0.07	-2.09	-0.24	-7.81	0.24	7.82
D_HbrSyd	Omitted									
Long-Haul Routes										
D_BneDrw	1.42	15.99	-0.03	-1.91	0.05	3.65	-0.02	-2.37	0.02	2.33
D_BnePer	0.03	1.57	-0.01	-1.83	0.01	2.06	0.00	0.01	0.00	0.03
D_DrwMel	1.08	13.24	0.01	0.30	0.02	1.26	-0.03	-2.45	0.02	2.35
D_DrwPer	1.48	13.96	0.07	3.78	0.01	0.39	-0.08	-6.86	0.08	6.87
D_DrwSyd	1.00	13.60	0.01	0.56	0.03	2.22	-0.04	-4.67	0.04	4.33
D_MelPer	0.25	20.47	0.07	16.12	-0.07	-17.68	0.00	0.06	0.00	-0.05
D_PerSyd	Omitted									

Appendix 4.1 Statistics for variables of flight delays and on-time models (N = 2,556)

Variable	Mean	Std. dev	Min	Max
Flight Frequency	425.23	453.71	2.00	2417.00
Load Factor (%)	77.74	6.96	51.70	96.60
Aircraft Size	164.72	33.62	62.00	276.00
Jet Fuel Price ($)	2.63	0.52	1.49	4.12
Low Cost Participation	0.14	0.17	0.00	1.00
HHI	0.43	0.12	0.13	1.00
Population (billion)	9570.00	10900.00	504.00	46000.00
Employment Rate	5309.51	268.43	4638.90	6088.72

Appendix 4.2 Hausman test - Flight delays in the flight departure model

```
                  ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |     fixed        random       Difference          S.E.
-------------+----------------------------------------------------------------
   log_SA_LF |    1.863464     1.819134        .0443299        .0351682
log_SA_Fli~t |    .0878586     .0643781        .0234805        .0131795
log_SA_Air~e |    .1193791     .1428625       -.0234834        .0279734
         HHI |    .1660021      .164906        .0010961        .0051209
log_SA_Jet~l |    .5333689     .5338324       -.0004635        .0037078
percent_Lo~t |     .063074     .0809971       -.0179231        .0094182
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       20.00
                Prob>chi2 =      0.0028
                (V_b-V_B is not positive definite)
```

Appendix 5.1 Data summary of the studied routes

Route	Route code	Route type	Passenger			Flight			Aircraft Size			Flight Delay		
			Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min
Melbourne-Adelaide	1312	Short_Haul	87,665	104,974	67,143	671	546	774	152	164	138	13.8%	24.0%	5.5%
Melbourne-Brisbane	1318	Medium_Haul	120,000	156,048	86,177	855	669	1,096	162	169	148	15.7%	31.8%	5.2%
Melbourne-Canberra	1317	Short_Haul	41,451	57,186	26,883	378	242	516	127	142	106	13.3%	26.3%	5.7%
Melbourne-Darwin	1315	Long_Haul	9,717	16,869	2,847	55	24	100	164	195	103	15.5%	52.4%	2.0%
Melbourne-Hobart	1316	Short_Haul	49,954	72,635	35,347	352	264	489	161	173	130	19.6%	33.6%	7.5%
Melbourne-Perth	1314	Long_Haul	75,470	100,572	45,688	411	265	564	205	232	178	20.2%	39.8%	9.5%
Melbourne-Sydney	1319	Short_Haul	310,000	384,699	243,353	1,847	1,309	2,417	186	199	173	17.0%	37.1%	7.3%

Appendix 5.2 3SLS outputs for flight frequency equation

	Short-Haul		Medium-Haul		Long-Haul	
Variable	Coef.	p-value	Coef.	p-value	Coef.	p-value
Flight frequency						
Pass	0.035	0.304	0.079	0.521	0.076	0.233
ASize	0.148	0.003	0.503	0.049	-0.117	0.316
Delay	0.003	0.809	0.010	0.456	0.074	0.019
Lag_Flight	0.832	0.000	0.530	0.000	0.725	0.000
HHI	0.005	0.714	-0.079	0.015	-0.152	0.000
Jet fuel	0.022	0.024	-0.009	0.620	0.081	0.006
LC Participation Rate	0.001	0.000	0.002	0.002	0.000	0.188
<u>Route (Route Code)</u>						
Melboune_Adelaide (1312)	0.000	(Omitted)				
Melbourne_Hobart (1316)	-0.097	0.000				
Melbourne_Canberra (1317)	-0.031	0.000				
Melboune_Sydney (1319)	0.078	0.000				
Melbourne_Brisbane (1318)			0.000	(Omitted)		
Melbourne_Perth (1314)					0.000	(Omitted)
Melbourne_Darwin (1315)					-0.102	0.011
Constant	0.294	0.032	0.663	0.119	0.501	0.000

Appendix 5.3 3SLS outputs for aircraft size equation

Variable	Short-Haul Coef.	Short-Haul p-value	Medium-Haul Coef.	Medium-Haul p-value	Long-Haul Coef.	Long-Haul p-value
Aircraft Size						
Pass	-0.003	0.832	0.131	0.001	0.074	0.003
Flight	0.042	0.002	0.059	0.149	-0.059	0.006
Delay	-0.004	0.376	-0.006	0.277	0.002	0.888
Lag_ASize	0.889	0.000	0.606	0.000	0.838	0.000
HHI	-0.001	0.930	0.003	0.855	-0.031	0.016
Jet fuel	-0.003	0.536	0.020	0.002	0.013	0.321
LC Participation Rate	0.000	0.039	0.000	0.014	0.000	0.589
Route (Route Code)						
Melboune_Adelaide (1312)	0.000	(Omitted)				
Melbourne_Hobart (1316)	0.021	0.010				
Melbourne_Canberra (1317)	-0.002	0.521				
Melboune_Sydney (1319)	-0.005	0.515				
Melbourne_Brisbane (1318)			0.000	(Omitted)		
Melbourne_Perth (1314)					0.000	(Omitted)
Melbourne_Darwin (1315)					0.003	0.873
_Constant	0.152	0.013	0.040	0.811	0.175	0.001

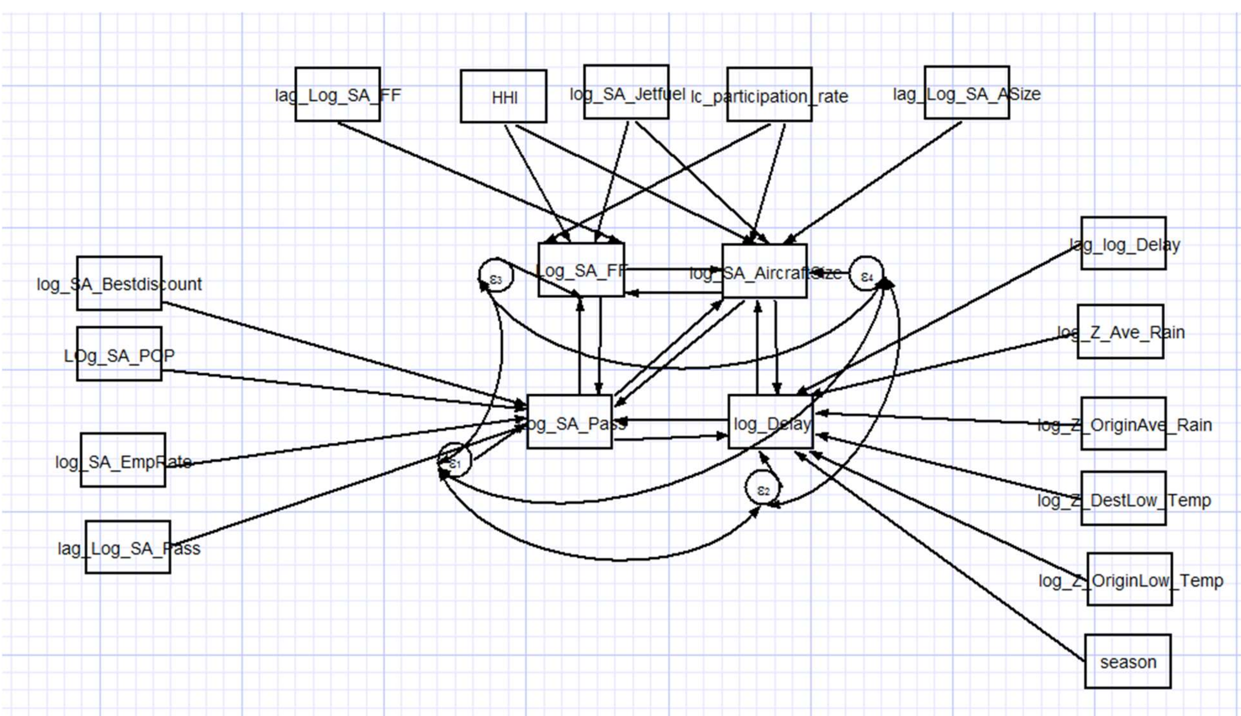
Appendix 5.4 3SLS outputs for flight delay equation

	Short-Haul		Medium-Haul		Long-Haul	
Variable	Coef.	p-value	Coef.	p-value	Coef.	p-value
Flight Delay						
Pass	0.052	0.743	0.169	0.832	0.151	0.601
Flight Delay	0.594	0.000	0.093	0.866	0.465	0.010
ASize	-0.039	0.866	3.229	0.031	-0.378	0.463
Lag_Delay	0.562	0.000	0.614	0.000	0.285	0.000
Origin_Low Temperature	0.019	0.457	0.013	0.795	-0.044	0.475
Dest_Low Temperature	-0.010	0.354	-0.005	0.696	0.007	0.669
Origin_Average Rain	0.050	0.000	0.054	0.038	-0.038	0.021
Dest_Average Rain	0.005	0.433	0.030	0.107	0.009	0.618
season						
2	0.008	0.617	0.021	0.504	-0.035	0.364
3	0.003	0.900	0.020	0.623	-0.030	0.544
4	0.003	0.812	0.003	0.903	-0.038	0.205
Route (Route Code)						
Melboune_Adelaide (1312)	0.000	(Omitted)				
Melbourne_Hobart (1316)	0.099	0.002				
Melbourne_Canberra (1317)	0.013	0.722				
Melboune_Sydney (1319)	0.005	0.929				
Melbourne_Brisbane (1318)			0.000	(Omitted)		
Melbourne_Perth (1314)					0.000	(Omitted)
Melbourne_Darwin (1315)					-0.227	0.069
Constant	-0.568	0.408	-5.850	0.020	0.407	0.411

Appendix 5.5 3SLS results

Equation	Observation	No. of parameters	RMSE	R-squared	Chi-squared
Short-Haul					
Pass	518	12	0.013288	0.9985	352559.8
Flight	518	10	0.016643	0.9968	160002.2
Aircraft Size	518	10	0.007373	0.9862	37036.68
Delay	518	14	0.102556	0.9048	4930.51
Medium-Haul					
Pass	132	9	0.013305	0.921	1600.8
Flight	132	7	0.010955	0.963	3650.69
Aircraft Size	132	7	0.004161	0.8936	1155.43
Delay	132	11	0.092972	0.6541	256.28
Long-Haul					
Pass	229	10	0.033247	0.995	52966.92
Flight	229	8	0.033434	0.9947	43667.64
Aircraft Size	229	8	0.014263	0.9629	6037.94
Delay	229	12	0.162679	0.9133	2410.31

Appendix 5.6 SEM model diagram



Appendix 5.7 Overall goodness of fit

Fit statistic	Value	Description
Likelihood ratio		
chi2_ms(266)	529.451	model vs. saturated
p > chi2	0.000	
chi2_bs(462)	8255.046	baseline vs. saturated
p > chi2	0.000	

Appendix 5.8 Equation-level goodness of fit

Equation	1312		1314		1315		1316		1317		1318		1319	
	R-squared	mc	R-squared	mc	R-squared	mc	R-squared	mc	R-squared	mc	R-squared	mc	R-squared	mc
Passenger	0.91	0.96	0.97	0.99	0.95	0.98	0.93	0.97	0.89	0.95	0.93	0.96	0.97	0.98
Flight delay	0.34	0.59	0.61	0.78	0.18	0.42	0.47	0.69	0.45	0.67	0.66	0.81	0.60	0.78
Flight Frequency	0.83	0.91	0.91	0.95	0.93	0.96	0.89	0.94	0.93	0.96	0.89	0.95	0.80	0.89
Aircraft Size	0.84	0.92	0.97	0.99	0.91	0.95	0.82	0.90	0.94	0.97	0.97	0.98	0.97	0.98