Highlights

* We investigate the market development in the most traveled regional airports in Australia.
* The availability of low-cost carrier services and international services contribute positively to market growth.
* Higher commodity price increases the traffic volume in markets heavily reliant on mineral resources.
* Appreciation of the Australian dollar decreases the passenger flow in tourism-dependent areas.
* Special consideration needs to be paid to regional airports to help deal with economic shocks and cover fixed costs.

Air Transport Services in Regional Australia: Demand pattern, frequency choice and airport entry

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ABSTRACT

In this study, we investigate the development of the aviation market at Australia’s top 50 regional airports during the 2005-2013 period. Our demand estimation results suggest that a higher commodity price increases the traffic volume in markets where the local economy is heavily reliant on mineral resources and that appreciation of the Australian dollar decreases the passenger flow in tourism-dependent areas. The presence of leading airlines and low-cost carriers and the availability of international services all contribute positively to market growth. Airport entry analysis reveals that the major carriers engage in clear strategic interactions. The Qantas airline group uses Jetstar as a fighting brand, such that Jetstar flies to a destination if and only if the regional airport is also served by Virgin Australia, the group’s major competitor. Unlike the routes connected to major airports, the demand at regional airports is not sensitive to flight frequency. Our empirical results support the introduction of a consistent aviation policy across Australia, especially for issues related to airline competition and demand stimulation. However, special consideration needs to be paid to regional airports to help them deal with economic shocks and cover fixed costs.

*Keywords*: Regional Australia, Regional airports, Airline entry, Flight frequency

1. **Introduction**

 As an input into numerous types of economic activity, including tourism, trade, and investment, air transport is an important factor in achieving economic development and welfare enhancement. Air services to distant and small markets are particularly important, because there is no close substitute for this travel mode due to the tyranny of distance (Pagliari 2010). This is particularly the case for Australia, which is geographically remote and large. Regional Australia accounts for about one third of the total population and two thirds of the national export income. Air services thus play a vitally important role in connecting the regional areas of Australia to the capital cities and the rest of the world by facilitating the movement of goods and people.

 In 2014, the passenger movement (the sum of passenger arrivals and departures) at Australian regional airports reached 24.3 million, an increase of 45% from 16.8 million in 2005. The total passenger movement in the domestic market was 115 million in 2014, an increase of 42.5% from 80.7 million in 2005. Much of the traffic is concentrated at the relatively large airports, with the top 50 regional airports handling 22.8 million passengers in 2014, or 94% of the total passenger movement at all regional airports (BITRE 2015). According to the Bureau of Infrastructure, Transport and Regional Economics (BITRE), the annual growth in passenger traffic at regional airports has been consistently higher than that at airports in major cities in the last 10 years.

 Many studies have examined the determinants of air traffic volume in metropolitan areas. Liu et al. (2006) contend that the likelihood of a major air passenger market emerging is primarily determined by the size of the metropolitan population and the levels of employment in professional, scientific, technical, and management services. Discazeaux and Polese (2007) examine the determinants of air traffic volume in the 89 largest urban areas in the U.S. and Canada, and confirm that urban size and the local industry structure remain the primary determinants. Dobruszkes et al. (2011) report that gross domestic product (GDP), the level of economic decision-power, tourism functions, and the distance from a major air market are the most important factors influencing air traffic flows in Europe. However, efficient and competitive aviation services can also increase traffic volumes by offering positive feedback to demand generation. Because increased flight frequency generally reduces passengers’ schedule delay (Douglas and Miller 1974), consumers’ willingness-to-pay and travel demand usually increase with flight frequency (Richard 2003, Fu et al. 2014). Strong airline competition often leads to lower prices and improved service quality, which substantially increase the traffic volume (Windle and Dresner 1996, 1999, Dresner et al. 1996, Fu et al. 2011, Adler et al. 2014).

 In comparison, less attention has been dedicated to the aviation markets at regional airports. Humphreys and Francis (2002) note the worldwide traffic concentration at large airports and underused capacity at regional airports. Graham and Guyer (2000) argue that the U.K. aviation policy largely focuses on capacity shortages at large airports in southeast England and the privatization and commercialization of the country’s airports, and contend that the issues affecting regional airports, such as sustainability and pro-competition policy, should be given more consideration. Humphreys and Francis (2002) examine the U.K. aviation market and conclude that regional airport performance depends greatly on the decisions of airlines. Thus, it is important to balance the interests of all stakeholders when formulating airport planning and regulatory policies. Forsyth (2006) simulates the costs and benefits of regional airport subsidies using a computable general equilibrium model, and argues that although it is possible for a region to enjoy economic gains as a result of an airport subsidy, the effect on nationwide welfare is uncertain. Adler et al. (2013) study the efficiency of 85 European regional airports via data envelopment analysis and second-stage regressions, and conclude that regional airports have inefficient daily operations, have failed to explore business opportunities, and have missed the opportunity to break even with small traffic volumes. Although these studies offer rich insights into the regional aviation issues, they do not directly analyze the market development patterns at regional airports. Airline services and traffic volumes are critically important factors in the management of an airport. Together, they directly determine the capacity use, operational costs, and airport revenue and indirectly determine the regulatory policies and regional economic development. Thus, it is important to examine the demand patterns and market dynamics to ensure that appropriate recommendations are made for regional airports.

 In this study, we aim to fill this gap by empirically examining the market development patterns in Australia’s top 50 regional airports during 2005-2013.[[2]](#footnote-2) The remainder of the study is organized as follows. In Section 2, we review Australia’s air transport policy and the aviation activities at regional airports. In Section 3, we describe the data and methods used to analyze the demand patterns, frequency choices, and airport entry decisions. In the final section, we summarize the key findings, discuss the policy implications, and suggest possible directions for future studies.

1. **Australia’s air transport policy and the aviation activity at regional airports**

 Since 1990, Australia has gradually removed the capacity, airfare, and market entry constraints and the limits on foreign ownership of domestic airlines. Interstate regional services have been completely deregulated and are now subject only to the competition laws that also apply to other industry sectors. Although the state and territory governments have the power to regulate intra-state air services, intra-state air services in Victoria, Tasmania, Northern Territory, and the Australian Capital Territory have been completely deregulated. Some low-volume routes in New South Wales, Queensland, South Australia, and West Australia are still subject to regulation. Low-volume routes are licensed on a one-route, one-license basis. Competition is encouraged on higher-volume routes where licensing is not required.

 By 2003, all of the major domestic airports in Australia had been privatized and formal price regulation replaced by “light-handed regulation” (Forsyth 2002, 2003; Yang and Fu 2015). The LeighFisher (2011) report notes that the overall cost levels at Australian airports are lower than those in North America and Europe. Forsyth (2004, 2008) and Assaf (2010) reached similar conclusions. In contrast to the good performance of major airports, the overwhelming majority of Australia’s regional airports, which are mainly owned by local governments and councils, are inadequately resourced to provide sufficient maintenance and infrastructure upgrade services and to attract qualified and skilled personnel (Donehue and Baker 2012). The Australian Airports Association estimates that up to 50% of regional airports operate at a loss each year and are heavily reliant on cross-subsidization from their local government owners (AAA 2012).

 The Australian Department of Infrastructure and Regional Development defines regional aviation as the scheduled commercial airline activity between regional areas or between regional areas and capital cities. Avstas (1999) defines regional airlines as those that provide scheduled regular public transport (RPT) services within Australia and link smaller rural centers with principal cities. The strict definition states that regional airlines use aircraft that contain 38 seats or fewer or have a payload of 4,200 kilograms or less. However, some airlines that use larger aircraft with 60-70 seats are still called regional airlines. Some regional areas are also serviced by jet aircraft from the major domestic airlines. The definitions of the metropolitan and regional areas in Australia are based on the Australian Standard Geographical Classification (ASGC) Remoteness Structure, which broadly divides the country into five regions: major cities, inner regional Australia, outer regional Australia, remote Australia, and very remote Australia. The last four classes are collectively designated as the “regional area,” and this designation is used in this study.

 Table 1 shows that the number of regional airports across all regions, from inner regional Australia to very remote Australia, declined between 1985 and 2009. From 2010, there was a rise in the number of airports with RPT air services in very remote Australia. Although some regional airports have lost RPT air services in the last few years, more new services have been added to other regional airports, resulting in a rebound of the total number of regional airports served. However, it should be noted that the sudden increase after 2010 may be due to a data collection problem, as the data on the number of regional airports in the very remote areas served by West Wing before 2009 are not available (BITRE 2012).

<Table 1 about here>

 Many of the regional airports in Australia compete to attract airlines. The number of airlines serving regional airports decreased from 33 in 2005 to 28 in 2010, and during this period more than 60% of the regional airports in Australia were served by only one airline (AAA 2012). BITRE (2012) reports that between 2008 and 2010, 7% of regional airports lost all of their RPT services and 30% lost some services. The corresponding figures for 2005 to 2008 are 25% and 21%, respectively. However, more than 40% of regional airports have received additional services in the last 10 years.

 BITRE (2013) suggests that air travel between the major cities and regional areas accounts for more than 90% of the entire regional aviation market. However, in 2012, the number of routes between regional airports (300) was much higher than the number of routes (176) between the major cities and regional airports, although 40% of the regional air routes had less than 1,000 passengers each year and 60% of the regional routes had less than three flights per week.

 To support the low volumes and the introduction of new routes to small and remote communities, the Australian government introduced the Airservices Australia Enroute Charges Payment Scheme, which provides subsidies to air operators that provide aeromedical services to regional and remote areas. Since September 2014, airlines operating commercial services to regional and remote areas have been able to apply for assistance under this scheme. In addition, the Australian Regional Aviation Access Program provides assistance for air transport access and safety upgrades in remote areas where air services are not commercially viable. However, the level of government assistance provided to the aviation industry has significantly decreased in the last two decades, and part of the assistance goes toward supporting new routes to regional communities that do not have air transport services. To increase revenue, most of the current regional airlines and airport air services have to rely on new technologies and efficiency improvements to contain costs and offer better services. Therefore, it is important to understand the market development patterns in regional Australia to assist the development of effective business strategies and public policies. For example, with the decline in the mineral resources sector due to the collapse of commodity prices in recent years, many resource-dependent towns have been abandoned and regional connectivity may be lost. Some tourism-dependent towns may face similar issues if there are large fluctuations in the exchange rates. Specific policies and financial support may be needed to address these issues, including re-regulation in some cases.

1. **Market analysis of Australian regional airports**

 To investigate the market development patterns in the Australian regional markets, we first jointly estimate reduced-form equations of travel demand and flight frequency. Our empirical findings allow us to identify the key macroeconomic determinants of the market outcomes at regional airports and the dynamic patterns of flight frequency and aircraft choice. As airport performance is significantly influenced by the operations of major airlines, we study airport entry for the major airlines in the Australian regional markets, including Qantas and its low-cost subsidiary Jetstar, and the other major carrier, Virgin Australia. Such investigations also allow us to identify any possible asymmetry effects of airport pricing and services on network airlines vs. low cost carriers (Fu et al. 2006, Oum and Fu 2007). In the following sections, we first describe the data and then explain the methodology and results obtained for each research module.

* 1. *Data description*

Two groups of factors, namely geo-economic and service-related factors, have been identified as the main drivers of air traffic demand (Jorge-Calderón 1997; Wang and Song 2010). Geo-economic factors consist of economic variables such as income and population and locational factors including the distance and other geographical characteristics of the area in which transportation takes place. Service-related factors include the quality and airfare components of aviation services (Wang and Song 2010). Studies have found that flight frequency is a key determinant of consumer surplus and airline market share, often based on pooled national data or routes out of metropolitan regions (see, for example, Windle and Dresner 1995, 1999; Drenser et al. 1996; Richard 2003; Fu et al. 2011; Homsombat 2014; Fu et al. 2015). However, few studies have validated this pattern in regional markets. In this study, we focus on the market performance of the top 50 regional airports in Australia using data on the 2005-2013 period. We collect a wide range of control variables, including macroeconomic variables such as local population and income, jet fuel, and aggregate airfare level; service attributes such as flight frequency and aircraft size; and market-specific variables such as the number of destinations connected to an airport, and the market shares of the major airlines at the airport level. Table 2 lists the dependent and independent variables and the data sources. Table 3 provides the summary statistics.

<Tables 2 & 3 about here>

 The exchange rate and commodity price variables are included because many regional Australian airports are close to popular tourism destinations or are situated in mining-dependent areas. Tourism tends to react strongly to fluctuations in the real exchange rate, regardless of the bilateral or multilateral indicators used (Culiuc 2014). The real effective exchange rate (REER), which measures the real value of a country’s currency against a basket of its trading partners’ currencies, may affect the travel decisions of both overseas tourists and Australian residents. As a domestic tourism destination may be a potential substitute for an overseas destination, the exchange rate may influence the visitor volumes in regional tourism cities. The interaction between a tourism destination dummy and the REER is considered in the demand equation. The commodity price index serves as an indicator of the prices received by Australian commodity exporters. Australia’s mining boom in the last decade is expected to affect passenger traffic flows in resource-dependent areas. Therefore, an interaction term between the mining variable and the commodity price is also included in the demand equation.

 The airfare index is constructed based on the fares collected monthly for the top 70 routes in the Australian domestic market by BITRE. We use the annual average index constructed by the lowest available economy class fare in our estimation. In theory, the use of this variable may cause an endogeneity problem. However, this fare index mainly captures the fare changes on the busiest routes between major cities, because passenger volumes are used as weights when constructing the index. Therefore, any endogeneity bias should be minimal.[[3]](#footnote-3)

 Airport-specific variables such as the number of destinations, number of airlines, and the average distance of the routes served out of an airport describe the network connectivity and service level at an airport. These variables are used in all of the empirical estimations described in the following sections. Airline/airport-specific variables such as the market shares of the leading airlines and/or a presence dummy at an airport are used to capture the possible effects of airline market power and traffic feeder operations. These variables may also cause endogeneity problems. However, because airline entry and competition mostly occur at the route level, and these variables are calculated at the airport level in our study, any endogeneity bias should be minimal.

 The names and airport codes for the top 50 airports used in our analysis are reported in Appendix 1.

*3.2 Demand determinants and flight frequency*

 Using an approach similar to those adopted by Schipper et al*.* (2002), Pitfield et al. (2010), and Wang et al. (2014), we simultaneously estimate demand and flight frequency equations to improve the estimation efficiency and control for the endogeneity between travel demand and flight frequency. The system of equations is specified as follows, where the subscript $i$ denotes the airport and subscript $t$ denotes the year. [[4]](#footnote-4)

(1.1) $lnTraffic\_{it}=α\_{0}+β\_{1}lnFlight\_{it}+δ\_{1}lnPop\_{it}+α\_{1}lnIncome\_{it}+δ\_{2}lnDist\_{t}+α\_{2}Tourism\_{i}+$

$$ α\_{3}Mining\_{i}+α\_{4}International\_{i}+δ\_{3}Exchange\_{t}+δ\_{4}Tourism\_{i}\*Exchange\_{t}+$$

$$ δ\_{5} lnCommodity\_{t}+δ\_{6}Mining\_{i}\*lnCommodity\_{t}+α\_{5}lnFare\_{t}+α\_{6}QantasShare\_{it}+$$

$$ α\_{7 }LCCShare\_{it}+α\_{8}NoDest\_{it}+α\_{9} lnYear\_{t}+η\_{1i}+ε\_{1it}$$

(1.2) $lnFlight\_{it}=ω\_{0}+ β\_{2}lnTraffic\_{it}+β\_{3}lnAircraftSize\_{it}+ω\_{1}lnIncome\_{it}+ω\_{2}Tourism\_{i}+ω\_{3}Mining\_{i}$

$$ +ω\_{4}International\_{i}+λ\_{1}lnJetfuel\_{t}+ω\_{5}lnFare\_{t}+ω\_{6}QantasShare\_{it}$$

$$+ω\_{7}LCCShare\_{it}+λ\_{2}NoAirline\_{it}+ω\_{8}NoDest\_{it}+ω\_{9}lnYear\_{t}+η\_{2i}+ε\_{2it}$$

The preceding system of equations is rewritten in the following expressions.

(2.1) $lnTraffic\_{it}=β\_{1}lnFlight\_{it}+X\_{it}α+Z\_{1it}δ+η\_{1i}+ε\_{1it}$

(2.2) ession, uations in the following ex$lnFlight\_{it}=β\_{2}lnTraffic\_{it}+β\_{3}lnAircraftSize\_{it}+X\_{it}ω+Z\_{2it}λ+η\_{2i}+ε\_{2it}$

The two equations can be denoted in matrix form, as shown in Eq. (3).

(3) $\left[\begin{matrix}1&-β\_{1}&0\\-β\_{2}&1&-β\_{3}\end{matrix}\right]\left[\begin{matrix}lnTraffic\_{it}\\lnFlight\_{it}\\lnAircraftSize\_{it}\end{matrix}\right]=\left[\begin{matrix}α&δ\\ω&λ\end{matrix}\right]\left[\begin{matrix}X\_{it}&X\_{i t}\\Z\_{1it}&Z\_{2it}\end{matrix}\right]+\left[\begin{matrix}η\_{1i}+ε\_{1it}\\η\_{2i}+ε\_{2it}\end{matrix}\right]$,

 The error terms $η\_{1i}$ and $η\_{2i}$ are the airport specific time invariant unobservables, and the error terms $ε\_{1it}$ and $ε\_{2it}$ are stochastic random errors. The variables $[lnTraffic\_{it}, lnFlight\_{it}, lnAircraft\_{it}]'$ are considered endogenous given that both theoretical and empirical airline studies indicate that there is a simultaneity among them (Richard 2002; Schipper et al. 2002; Zhang 2014). $Υ\_{it}=[X\_{i t} ,Z\_{1it}, Z\_{2it}]'$ are exogenous variables in the demand and flight frequency equation system that satisfy the mean independence condition $E\left[Υ\_{it}ε\_{it}\right]=0$ and $ε\_{it}=[ε\_{1it},ε\_{2it}]'$**.** We do not assume mean independence between $Υ\_{it}$and $η\_{i}$, because we use a fixed effects (FE) model to deal with the potential endogeneity problem in the case of $ E[Υ\_{it}η\_{i}]\ne 0$.

 In the demand equation, the aircraft size variable (i.e., $AircraftSize\_{it}$) is not included because the additional comfort offered by large aircraft is likely to be minor in short regional markets. We use the flight frequency variable $lnFlight\_{it}$ to control for passenger schedule delay. $X\_{it}$representsthe common exogenous variables determining both demand and frequency, whichinclude $lnIncome\_{it}$, $Tourism\_{i}$, $Mining\_{i}$, $International\_{i}$, $lnFare\_{it}$, $QantasShare\_{it}$,$ LCCShare\_{it}$, and $lnNoDest\_{it} $(see Table 2 for the definitions of the variables). $lnIncome\_{it}$ is a proxy for the wealth level of local air passengers. With higher income passengers consume more air travel and tend to place higher value on flight frequency (Brueckner and Flores-Fillol 2007; Wang et al. 2014). $Tourism\_{i}$, $Mining\_{i}$, and $International\_{i}$ capture the attributes of the airports that could affect the airline demand and flight frequency decisions. It is also expected that the market share variables, $QantasShare\_{it}$ and$ LCCShare\_{it}$, influence both equations. In addition, we use $lnYear\_{t}$ to control for any time trends during the sample period in the two equations. $Z\_{1it}$comprises exogenous variables that affect travel demand but not flight frequency, namely, $lnPop\_{it}$, $lnDist\_{i}$, $Exchange\_{t}$, $Tourism\_{i}\*Exchange\_{t}$, $lnCommodity\_{t}, $and $Mining\*lnCommodity\_{t}$. The population variable measures the market size, which does not directly affect the flight frequency when the travel demand is controlled for (Schipper 2012). $lnDist\_{i}$ denotes the distance from the regional airport to the capital city of the state, which mainly affects the travel demand. The exchange rate and commodity price variables, $Exchange\_{it}$, $Tourism\_{i}\*Exchange\_{it}$, and $lnCommodity\_{t}$ , can influence tourism air passengers’ willingness to pay and the utility of the air travel for business purposes related to commodity trading. These variables should have much greater direct effects on air travel demand than the airline flight frequency strategies.

 We include the endogenous variables $lnTraffic\_{it}$ and $lnAircraft\_{it}$ in the flight frequency equation because airlines accommodate changes in passenger volumes by adjusting the flight frequency and there is a negative relationship between flight frequency and aircraft size. $ Z\_{2it}$includes flight frequency determinants that do not directly affect the travel demand. The jet fuel price (i.e., variable $Jetfuel\_{t}$) should affect the flight frequency through the airline fuel costs, which is the major flight-specific cost item. The changes in an airline’s flight cost directly affect the airline’s flight supply but not the airport demand (Fu et al. 2014). In addition, the number of airlines serving a regional airport (i.e., $NoAirline\_{it}$) can affect the airport aggregate flight frequency more than the airport aggregate demand. The so-called S-curve effect in flight frequency suggests that airlines that achieve a frequency-share advantage attain disproportionally higher market shares (Fruhan 1972). According to Binggeli and Pompeo (2006), such an S-curve is present in the U.S. domestic markets at the airport level, which means that the airlines tend to have a strong incentive to increase the flight frequency at an airport. Therefore, we should expect that more airlines competing at an airport contributes to higher aggregate flight frequency. Because we have controlled for the carriers’ market share in the demand function, the airline competition effect represented by the number of airlines $NoAirline\_{it}$ should be more strongly associated with the flight frequency.

 We use an equation-by-equation estimation method. For the demand equation estimation, the exogenous variables $Z\_{2it}=(lnJetfuel\_{t},NoAirline\_{it})$ can be used as instrumental variables for the endogenous variable $lnFlight\_{it}$ because they are included in the frequency equation but not in the demand equation. For the frequency equation estimation, the exogenous variables $Z\_{1it}=(lnPop\_{it}$, $lnDist\_{i}$, $Exchange\_{t}$, $Tourism\_{i}\*Exchange\_{t}$, $lnCommodity\_{t}$, $Mining\*lnCommodity\_{t}) $can be used as instrumental variables for the endogenous variables $lnTraffic\_{it}$ and $lnAircraft\_{it}$. To verify and select the appropriate instrumental variables from $Z\_{1it}$and $Z\_{2it}$, we conducted the Sargan-Hansen test (see Appendix 2). The test results show that $Z\_{2it}=(Jetfuel\_{it}, NoAirline\_{it})$ are valid instruments for flight frequency in the traffic demand function, and that a subset of the exogenous variables $Z\_{1it}$,$Z\_{3it}=(lnPop\_{it}$, $lnDist\_{it}$, $Exchange\_{it}$, $Tourism\_{i}\*Exchange\_{it})\in Z\_{1it}$are valid instrumental variables for the traffic demand and aircraft size in the flight frequency equation. The variables ($lnCommodity\_{t}$, $Mining\*lnCommodity\_{t}$) are not valid instruments for the traffic and aircraft size in the frequency equation. A fixed effects (FE) approach is then used to control for potential endogeneity by allowing $Υ\_{it}$to correlate with the airport-specific time-invariant unobservables $η\_{i}$. The first step of this FE approach is to demean the equations as follows to remove the time-invariant airport specific unobservables $η\_{i}$

(4.1) $lnTraffic\_{it}-\overbar{lnTraffic\_{i}}=β\_{1}(lnFlight\_{it}-\overbar{lnFlight\_{i}})+(X\_{it}-\overbar{X}\_{i})α+(Z\_{1it}-\overbar{Z}\_{1i})δ+(ε\_{1it}-\overbar{ε}\_{1i})$

(4.2) $lnFlight\_{it}-\overbar{lnFlight\_{i}}=β\_{2}(lnTraffic\_{it}-\overbar{lnTraffic\_{i}})+β\_{3}(lnAircraftsize\_{it}-\overbar{lnAircraftsize\_{i}}$

$$+(X\_{it}-\overbar{X}\_{it})ω+(Z\_{2it}-\overbar{Z}\_{2it})λ+(ε\_{2it}-\overbar{ε}\_{2i})$$

$Z\_{2it}-\overbar{Z}\_{2it}$can serve as instrumental variables to identify parameters $β\_{1}$, $α$, and $δ$in the demand equation, and $Z\_{3it}-\overbar{Z}\_{3i}$can also serve as instruments to identify parameters $β\_{2}$, $β\_{3}$, $ω$,and$λ$ in the frequency equation using a two-stage least squares estimation (2SLS). In addition to the FE model, a random effects (RE) specification is used to estimate the equations (2) with the assumption of $E\left[Υ\_{it}η\_{i}\right]=0$. If this assumption holds, then the RE model is more efficient than the FE estimation. Table 4 reports the estimation results from both models. The first-stage estimation results of the 2SLS are shown in Appendix 3.[[5]](#footnote-5)

<Table 4 about here>

 It should be noted that because airline competition mainly occurs at the route level, the estimation of the regional airport demand and airline flight frequency may be more accurate if route level data are used. Due to the unavailability of the route level data, we approximate the route level demand and flight frequency by using the average demand and average flight frequency, which are obtained by dividing the total airport demand and frequency by the total number of destinations out of an airport. Using the average demand $lnTraffic\\_ave\_{it}$, and flight frequency $lnFlight\\_ave\_{it}$ as dependent variables, we run the estimation again, with the results collated in Appendix 4. It can be seen that the estimation results are largely consistent with those reported in Table 4 when airport aggregate data are used. Therefore, the following discussion is based on Table 4.

Consistent with previous studies, local population and income have positive signs. The “population” variable is significant in the RE estimation, and the “income” variable is significant in both the FE and RE models. The interaction terms in both the FE and RE models are statistically significant. Higher commodity prices resulted in higher passenger movements in the mining-dependent areas during the sample period. In comparison, a higher exchange rate deterred overseas visitors from visiting Australian resorts and encouraged Australian residents to visit international destinations.

 The domestic airfare index is significantly positive in both the FE and RE models. As mentioned earlier, this index mainly captures the price changes on routes between major cities. Because regional aviation often serves as a traffic feeder to network carriers’ hub-and-spoke networks, it is possible that higher yields on the trunk routes allowed the major airlines to cross-subsidize the regional services or to jointly price services in the trunk and regional segments to explore network effects. Moreover, competition between Qantas and Virgin Australia, the two largest airlines in the domestic market, has been strong in the last few years. Therefore, it is also possible that the fare increase on the trunk routes was caused by a general rise in aviation demand instead of airline market power. Because air transport is a derived demand, the nationwide fare index may be interpreted as a proxy for the unobserved demand drivers in our analysis. If airline-specific fares can be obtained for all domestic routes, an in-depth analysis of this issue could lead to fresh insights. At the current stage this particular estimation result should be evaluated with caution.

 The demand equation estimates also suggest that Qantas and other low-cost carriers (LCCs) play an important role in boosting the air travel in regional markets. Qantas has a well-developed network and a large fleet of regional/narrow-body aircraft. This allows the carrier to feed traffic to its network with efficient operations or to offer cost-effective services on a large scale. The cost advantage of LCCs enables them to offer competitive prices. As a result, they drive up the traffic volumes at regional Australian airports. The RE model reports that regional airports with international flights had higher passenger flows during the sample period. This was also the case for the airports in tourism-rich areas. Mining towns usually have lower traffic movement because they are mostly located in sparsely populated areas. The number of destinations connected to a regional airport has insignificant effects in both models. This seems to suggest that only the flights to hub airports mattered, because the routes to additional destinations did not attract significantly more travelers. Passenger itinerary data are needed for a more detailed investigation.

 It is somewhat surprising to observe that a higher flight frequency did not significantly increase the air passenger volume at regional airports. In comparison, the elasticity of demand to flight frequency is estimated to be 0.79 for interstate European routes (Schipper et al. 2002), 1.021 for North Atlantic markets (Pitfield et al. 2010), and 0.945 in major Chinese routes (Wang et al. 2014). These estimates, which are mostly based on trunk route data, suggest that higher frequency stimulates demand. Our findings for the regional markets suggest that the travel demand is insensitive to frequency. The estimation results of the frequency equation in Table 4 show that the elasticity of flight frequency to airport traffic is 1.07 by the FE model and 0.878 by RE model. This implies that *ceteris paribus*, most airport traffic changes can be accommodated by flight frequency increases and slightly larger aircraft. This pattern can be identified in Figures 1 and 2, which depict the distributions of frequency and aircraft size at the sample airports. Over the sample period, there were moderate increases in total frequency and aircraft size.

<Figures 1 & 2 about here>

 As shown in Figure 3, among the major airlines serving regional airports, Jetstar used the largest aircraft on average, most of which were part of its A320 series narrow-body fleet. In comparison, although Virgin Australia initially used a similar aircraft mix, the carrier’s average fleet size decreased slightly over time. Qantas used mostly small regional aircraft owned by its regional aviation arm, QantasLink. As shown in Figure 4, Virgin’s market share increased from less than 10% to about 20% over the sample period, and the combined market share of Qantas and Jetstar also increased slightly. This resulted in the aggregate share of the top three airlines increasing from 60% to 76% at the expense of other niche competitors. Therefore, the increase in average aircraft size at Australian regional airports can largely be attributed to the higher market penetration by Virgin, Jetstar, and Qantas. The operations and airport choices of these three airlines play critical roles in shaping the market outcomes at regional airports.

<Figures 3 & 4 about here>

*3.3. Entry patterns of airlines at regional airports*

 Because the operations of major airlines significantly affect the overall performance of an airport, in this section, we investigate the airport entry patterns of the three leading carriers in the Australian regional market, namely Qantas (QF), Jetstar (JQ) and Virgin Australia (VA). Table 5 reports the summary statistics of the airport entry patterns of these carriers during the sample period. According to Table 5(a), in every year of the sample period, Jetstar served a regional airport if and only if Virgin Australia also served that airport. Homsombat et al. (2014) investigate airline pricing and route entry patterns in the Australian domestic market during 2009-2011, and conclude that Qantas used Jetstar as a fighting brand against other LCCs. Our analysis confirms that such a strategy has been consistently applied for extended periods in the regional markets.

<Table 5 about here>

 To systematically investigate the airport choice patterns of airlines in regional markets, we estimate a probit model for Qantas, Jetstar, and Virgin Australia, respectively. Qantas and Jetstar both belong to the Qantas airline group and have interconnected loyalty programs. Their main competitor is Virgin Australia, a carrier that started as an LCC but has progressively transformed into a full-service carrier.[[6]](#footnote-6) The probit model specification is similar to those that Homsombat et al. (2014), Fu et al*.* (2015), and Wang et al. (2016) use to analyze the route entry decisions of airlines, except that we are primarily interested in airport choice in this study. For example, Eq. (5) is estimated for Qantas as follows.

(5) $Qantas\_{it}=φ\_{0}+φ\_{1}lnPop\_{it-r}+φ\_{2}lnIncome\_{it-r}+φ\_{3}Tourism\_{i}+φ\_{4}Mining\_{i}$

$$ +φ\_{5}lnFare\_{t-r}+φ\_{6}Virgin\_{it-r}+φ\_{7}Jetstar\_{it-r}+ φ\_{8}Others\_{it-r}$$

$ +φ\_{9}lnYear\_{t}+ξ\_{it}$

 In the above entry estimation, $lnFare\_{t}$ measures the price level of the major trunk routes. The airline dummies $Virgin\_{it}$ and $Jetstar\_{it}$, and the number of other airlines ($Others\_{it})$, which measure the market competition dynamics, may be affected by the entry decision of Qantas *ex post*. Therefore, we use the lagged values of these explanatory variables in the estimation (with the subscript $t-r$ in Eq. (5)). These lagged variables are considered to be exogenous because although airlines usually start to evaluate the market conditions in advance, the final entry occurs within one or two years. In our estimations, we use one-year and two-year lagged values of the time variant variables, and the estimation results are presented in Table 6.

 The estimations using one-year and two-year lagged variables produce consistent results. Due to the entry pattern observed in Figure 5(a), the effect of Virgin’s presence on Jetstar’s entry decision cannot be statistically identified. This is because Jetstar only enters airports in which Virgin operates, there is no variation in the presence variable of Virgin, which makes it impossible to obtain the coefficient in this nonlinear probit estimation. This is also the case when we study the effect of the presence of Jetstar on the entry of Virgin.

 It is clear that all three airlines preferred to serve airports with strong aviation demand, as evidenced by the significantly positive coefficients of population, income, and tourism destination. Both Jetstar and Virgin avoided mining destinations, probably because the fleets of these LCCs were composed of mostly narrow-body aircraft that were not sufficiently cost-effective to serve such small destinations. The regional arm of Qantas, QantasLink, had more regional aircraft that were ideal for thin routes. The estimation results also reveal some strategic airport choice behavior. The Qantas airline group (Qantas + Jetstar) clearly used Jetstar as a fighting brand to compete with LCCs. The presence of Qantas decreased the likelihood of Jetstar service at the same airport to avoid service overlap (the coefficient of the variable *Qantas* in Jetstar’s airport entry estimation is significantly negative), because Jetstar provided services at all of the airports served by Virgin Australia in all of the sample years. The Qantas airline group was the clear market leader, controlling more than half of the domestic market. This probably explains why the presence of other airlines had negative effects on the entry decisions of Qantas and Jetstar yet no influence on Virgin Australia.

 In additional to the simple probit model estimation, we run a panel data probit model to account for the airport effect on airlines’ airport entry decisions. Let $ξ\_{it}=τ\_{i}+υ\_{it}$ , where $τ\_{i}$ is the airport effect in the entry model. Suppose that $τ\_{i}$ is the mean independent of the explanatory variables, a random probit model can be estimated to control for the airport-specific effect $τ\_{i}$ (Heckman and Willis 1976; Heckman 1981).[[7]](#footnote-7) We also allow $ξ\_{it}$ to follow autocorrelation in the time series and estimate the AR(1) model (Liang and Zeger 1986). The results of these additional probit model estimations are summarized in Appendix 5. These alternative probit model estimations provide largely consistent results, as does our simple probit model estimation, thus proving the robustness of our findings.

**4. Conclusions**

 Regional Australia accounts for one third of Australia’s population and contributes significantly to the national economy. In the last decade or so, many regional areas in Australia have become increasingly dependent on the tourism and mining industries, thus making efficient and reliable air transport services indispensable in these areas. Although many studies have discussed the economic and policy implications of regional aviation, the market development patterns at regional airports remain under-examined. In this study, we aim to fill this research gap by empirically investigating the Australian domestic market using data from the top 50 regional airports during 2005-2013.

 The estimation results of our demand and frequency equations suggest that similar to the aviation markets in major cities, local population and income are two important drivers of travel demand. Increased commodity prices lead to a rise in passenger movement at regional airports where the local economy relies heavily on mineral resources. Appreciation of the Australian dollar leads to a decrease in the passenger flow in tourism-dependent areas. The presence of leading airlines such as Qantas, and increased LCC services and direct international services contribute positively to the expansion of local markets. Moreover, our airport entry analysis reveals that the major carriers clearly engage in strategic interactions. The Qantas airline group used Jetstar as a fighting brand, having it serve an airport if and only if that airport was also served by Virgin Australia. Competition from other niche airlines had a negative effect on the airport entry decisions of the market leader (i.e., the Qantas airline group), but no significant effects on the market follower Virgin Australia. All of these findings are broadly consistent with the patterns observed in major airports.

 Our analysis also provides preliminary evidence of some of the distinctive features of Australia’s regional market. In particular, local demand is not sensitive to flight frequency, even though traffic volume growth is mostly served by flight frequency increase. Overall, individual airlines do not use significantly larger aircraft. The moderate growth in average aircraft size observed during the sample period was mainly a result of the higher LCC market share.

 Our study may lead to some important policy debates. The similar patterns observed in regional airports and metropolitan areas suggest that a consistent aviation policy can be developed for the whole of Australia, especially in regard to issues related to airline competition and demand stimulation. However, special consideration needs to be made for regional airports, because they can be vulnerable to economic shocks such as commodity price and exchange rate volatility. The government could intervene and re-regulate some of the regional routes that have been seriously affected by the decline of the mining industry. In addition, regional services can be sensitive to the performance of major routes, probably due to the network effects or inter-firm competition of airlines. Moreover, because flight frequency does not seem to play an important role in the regional market, government subsidies could be paid out as lump sums where justified instead of on a per-flight basis to offset fixed costs.

 Although our analysis has produced rich results, reduced-form equations have relatively weak power to identify causal effects. If more detailed airline-route specific data become available, structured models should be developed to validate our preliminary findings. This would be a valuable extension of our research, albeit one that is beyond the objectives of this study.

**References**

AAA, 2012. Australia’s regional airports: Facts, myths and challenges. Australian Airport Association, ACT.

Adler N., Fu X., Oum T.H., Yu C. 2014. Air transport liberalization and airport slot allocation: The case of the Northeast Asian transport market. Transportation Research - Part A, 62, 3-19.

Adler, N., Ülkü T., Yazhemsky, E., 2013. Small regional airport sustainability: Lessons from benchmarking. Journal of Air Transport Management 33, 22-31.

Assaf. A., 2010. The cost efficiency of Australian airports post privatisation: A Bayesian methodology. Tourism Management 31 (2), 267-273.

Avstats, 1999. Avstats web site. <http://www.dot.gov.au/aviation/avstats.htm>, Commonwealth Department of Transport and Regional Development, Canberra.

Binggeli, U., Pompeo, L., 2006. Does s-curve still exist? Technical report, McKinsey & Company.

BITRE, 2012. Air Transport service trends in regional Australia (2011 update). Research Report 130, Bureau of Infrastructure, Transport and Regional Economics, Department of Infrastructure and Regional Development, Australian Government.

BITRE, 2013. Air Transport service trends in regional Australia (2013 update). Information Sheet 47, Bureau of Infrastructure, Transport and Regional Economics, Department of Infrastructure and Regional Development, Australian Government.

BITRE, 2015. Statistical report: Domestic aviation activity annual 2014. Bureau of Infrastructure, Transport and Regional Economics, Department of Infrastructure and Regional Development, Australian Government.

Brueckner. J.K., Flores-Fillo, R., 2007. Airline schedule competition. Review of Industrial Organization 30, 161-177.

Culiuc, A. 2014. Determinants of international tourism. IMF Working Paper No. 14/82. Available at SSRN: [http://ssrn.com/abstract=2445467](http://ssrn.com/abstract%3D2445467).

Donehue, P., Baker, D., 2012. Remote, rural and regional airports in Australia. Transport Policy 24, 232-239.

Douglas, G., Miller, J.C., 1974. Quality competition, industry equilibrium and efficiency in the price-constrained airline market. American Economic Review 64 (4), 657-669.

Dresner, M., Lin, J.S.C., Windle, R., 1996. The impact of low-cost carriers on airport and route competition. Journal of Transport Economics and Policy 30, 309-328.

Forsyth, P., 2002. Privatisation and regulation of Australian and New Zealand airports. Journal of Air Transport Management 8 (1), 19-28.

Forsyth, P., 2003. Regulation under stress: Developments in Australian airport policy. Journal of Air Transport Management 9 (1), 25-35.

Forsyth, P., 2004. Replacing regulation: Airport price monitoring in Australia. In: Forsyth, P., Gillen, D., Knorr, A., Mayer, O., Niemeier, H.-M., Starkie, D. (Eds.), The Economic Regulation of Airports: Recent Developments in Australasia, North America and Europe. Ashgate, Aldershot.

Forsyth, P., 2006. Estimating the costs and benefits of regional airport subsidies: A computable general equilibrium approach. Paper presented at German Aviation Research Society Workshop, Amsterdam 2006.

Forsyth, P., 2008. Airport policy in Australia and New Zealand: Privatization, light-handed regulation and performance. In: Winston, C., de Rus, G. (Eds.), Aviation Infrastructure Performance: A Study in Comparative Political Economy. Brookings Institution Press, Washington, DC.

Fruhan, W.E., 1972. The fight for competitive advantage. Harvard University, Boston.

Fu, X., Dresner, M., Oum, T.H., 2011. Effects of transport service differentiation in the U.S. domestic airline market. Transportation Research Part E 47 (3), 297-305.

Fu, X., Lei, Z., Wang, K., Yan J., 2015. Low cost carrier competition and route entry in an emerging but regulated aviation market: The Case of China, Transportation Research - Part A, 79, 3-16.

Fu, X., Lijesen M., Oum, T.H., 2006. An analysis of airport pricing and regulation in the presence of competition between full service airlines and low cost carriers, Journal of Transport Economics and Policy 40(3), 425–447.

Fu, X., Oum, T.H., Yan, J., 2014. An analysis of travel demand in Japan’s inter-city market: Empirical estimation and policy simulation. Journal of Transport Economics and Policy 48(1), 97-113.

Garin-Munoz, T., 2006. Inbound international tourism to Canary Islands: A dynamic panel data model. Tourism Management, 27(2), 281-291.

Graham, B., Guyer, G. 2000. The role of regional airports and air services in the United Kingdom. Journal of Transport Geography 8, 249-262.

Heckman, J.J., Willis, R.J., 1976. Estimation of a stochastic model of reproduction: An econometric approach. In: Household Production and Consumption. NBER, pp. 99-146.

Heckman, J.J., 1981. Statistical models for discrete panel data. In: Manski, C., McFadden, D. (Eds.), Structural Analysis of Discrete Data with Econometric Applications. MIT Press, Cambridge, MA.

Homsombat, W., Lei, Z., Fu, X., 2014. Competitive effects of the airlines-within-airlines strategy: Pricing and route entry patterns. Transportation Research - Part E 63, 1-16.

Humphreys, I., Francis, G. 2002, Policy issues and planning of UK regional airports, Journal of Transport Geography 10, 249-258.

Jorge-Calderón, J.D. 1997. A demand model for scheduled airline services on international European routes. Journal of Air Transport Management, 3 (1), 23-35.

Liang, K.Y., Zeger, S.L., 1986. Longitudinal data analysis using generalized linear models. Biometrika 73, 13-22.

Little child, S.C., 2012. Australian airport regulation: Exploring the frontier. Journal of Air Transport Management 21, 50-62.

Oum, T.H., Fu X., 2007. Air transport security user charge pricing: An investigation of flat per-passenger charge vs. ad valorem user charge schemes, Transportation Research - Part E 43(3), 283-293.

Pagliari, R., 2010. Trends in air service development within the highlands and islands of Scotland 1983-2006. In George Williams and Svein Brathen (eds), Air Transport Provision in Remoter Regions, Ashgate, England, 21-46.

Pitfield, D.E., Caves, R.E., Quddus, M.A., 2010. Airline strategies for aircraft size and airline frequency with changing demand and competition: A simultaneous equations approach for traffic on the North Atlantic. Journal of Air Transport Management 16, 151-158.

Richard, O., 2003. Flight frequency and mergers in airline markets. International Journal of Industrial Organization 21, 907-922.

Schipper, Y., Rietveld, P., Nijkamp, P., 2002. European airline reform: An empirical welfare analysis. Journal of Transport Economics and Policy 36, 189-209.

Wang, K., Gong, Q., Fu, X., Fan, X., 2014. Frequency and aircraft size dynamics in a concentrated growth market: The case of the Chinese domestic market. Journal of Air Transport Management, 36, 50-58.

Wang, K., Tsui, K.W.H., Liang, L., Fu, X., 2017. Entry patterns of low-cost carriers in Hong Kong and implications to the regional market. Journal of Air Transport Management. In press.

Wang, M., Song, H., 2010. Air travel demand studies: A Review. Journal of China Tourism Research, 6(1), 29-49.

Windle, R., Dresner, M., 1995. The short and long run effects of entry on US domestic air routes. Transportation Journal 35 (2), 14-25.

Windle, R., Dresner, M., 1999. Competitive responses to low cost carrier entry. Transportation Research Part E 35 (1), 59-75.

Yang, H., Fu, X., 2015. A comparison of price-cap and light-handed airport regulation with demand uncertainty, Transportation Research - Part B, 73, 122-132.

York Aviation, 2004. The social and economic impact of airports. Airports Council International-Europe, Geneva.

Zhang, Y., 2014. The puzzle of aircraft size and traffic growth. Journal of Transport Economics and Policy 48(3), 465-482.

**Table 1**

Number of regional airports served, by the Australian Statistical Geographic Classification (ASGC) Remoteness Classification.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Airports by ASGC Remoteness Classification | **1985** | **1990** | **1995** | **2000** | **2005** | **2008** | **2009** | **2010** | **2011** | **2012** |
| Inner regional Australia | 43 | 38 | 40 | 37 | 29 | 24 | 25 | 25 | 27 | 26 |
| Outer regional Australia | 47 | 43 | 36 | 36 | 31 | 27 | 28 | 27 | 27 | 28 |
| Remote Australia  | 38 | 32 | 31 | 22 | 21 | 19 | 17 | 15 | 15 | 16 |
| Very remote Australia | 136 | 95 | 100 | 86 | 88 | 67 | 82 | 81 | 82 | 101 |
| Total  | 264 | 208 | 207 | 181 | 169 | 137 | 152 | 148 | 151 | 171 |

Source: Adapted from BITRE (2013)

**Table 2**

Explanations of the variables and data sources.

|  |  |  |  |
| --- | --- | --- | --- |
| Variable | Notation | Explanation  | Data source  |
| Passenger traffic | $$Traffic\_{it}$$ | The sum of annual passenger arrivals and departures at a regional airport for the period 2005-2013. The sample comprises the top 50 regional airports in terms of passenger movements in 2014 | Airport traffic data reported by the Bureau of Infrastructure, Transport and Regional Economics (BITRE), the Department of Infrastructure and Regional Development of Australian Government  |
| Flight frequency | $$Flight\_{it}$$ | The yearly aggregate airport total scheduled flight frequency for domestic flights, including outbound and inbound | The Official Airline Guide (OAG) |
| Aircraft Size | $$AircraftSize\_{it}$$ | The average aircraft size of the airport, calculated by dividing the airport aggregate seats by the aggregate flight frequency | OAG |
| Population  | $$Pop\_{it}$$ | Resident population by local government area (LGA) where the airport is located | Australian Bureau of Statistics (ABS): Regional Population Growth (cat no. 3218.0), Australia, March 2015  |
| Income | $$Income\_{it}$$ | Average annual wage and salary income in the LGA where the airport is located  | ABS: The [Wage and Salary Earner Statistics for Small Areas, Time Series, 2005-06 to 2010-11](http://www.abs.gov.au/AUSSTATS/abs%40.nsf/Lookup/5673.0.55.003Main%2BFeatures12005-06%20to%202010-11) (cat no. 5673.0.55.003 2005-06) 2013.The data for 2011-2013 were estimated by the authors based on the growth rate of wage and salary income between 2005 and 2010 |
| Distance  | $$Dist\_{t}$$ | The distance from the regional airport to the capital city of the state | Australian air distances published by the Bureau of Infrastructure, Transport and Regional Economics (BITRE), the Department of Infrastructure and Regional Development of Australian Government |
| Tourism  | $$Tourism\_{i}$$ | A dummy variable indicating whether or not tourism is a major industry in an airport’s catchment area | Local government websites  |
| Mining  | $$Mining\_{i}$$ | A dummy variable indicating whether or not mining is a major industry in an airport’s catchment area | Local government websites |
| International  | $$International\_{i}$$ | A dummy variable denoting whether or not there is a presence of international flights at an airport based on year 2013 data | Airport website |
| Exchange rate | $$Exchange\_{t}$$ | The real effective exchange rate (REER), which measures the real value of a country’s currency against the basket of the trading partners of the country  | World Bank Global Economic Monitor |
| Commodity price | $$Commodity\_{t}$$ | Index of commodity prices, which is the weighted average of recent changes in commodity prices, where the weight given to each commodity reflects its importance in relation to the total commodity export value in a base period | Reserve Bank of Australia (RBA) |
| Jet fuel | $$Jetfuel\_{t}$$ | U.S. Gulf Coast kerosene-type jet fuel spot price FOB (annual average) | U.S. Energy Information Administration |
| Air fare  | $$Fare\_{t}$$ | BITRE’s domestic air fare index (annual average). Fares are collected for the top 70 routes in the Australian domestic network | Compiled by BITRE, the Department of Infrastructure and Regional Development of Australian Government. |
| Qantas Share | $$QantasShare\_{it}$$ | The share of scheduled seats of Qantas in each regional airport | Calculated by authors using the OAG data |
| LCC Share  | $$LCCShare\_{it}$$ | The share of scheduled seats of all LCCs in each regional airport | Calculated by authors using the OAG data. LCC classification from CAPA is used.  |
| No. of Destination | $$NoDest\_{it}$$ | The number of destinations served by this regional airport | Calculated by authors using the OAG data |
| No. of Airlines | $$NoAirline\_{it}$$ | The number of airlines operating at this regional airport | Calculated by authors using the OAG data |
| Qantas / Virgin /Jetstar | $$Qantas\_{it}$$/$Virgin\_{it}$/$Jetstar\_{it}$ | A dummy variable that equals 1 if a Qantas / Virgin/ Jetstar airline operates in this airport | OAG |
| Others |  | The number of other regional/ charter airlines operating at this regional airport  | OAG |

**Table 3**

Summary statistics of the variables.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Variable | Obs. | Mean |  | Std. Dev. | Min | Max |
| Traffic (person) | 450 |  401,635  |  |  643,125  |  5,417  |  4,200,000  |
| Flight (number) | 450 |  6,196  |  |  6,189  |  302  |  39,458  |
| Seats (number) | 450 |  543,928  |  | 758,960  | 11,430  |  5,033,602  |
| Aircraft Size (seat) | 450 |  76  |  |  39  |  14  |  166  |
| Population (person) | 450 |  40,766  |  |  35,491  |  500  |  189,017  |
| Income (AU$) | 450 | 49,829  |  |  13,880  | 29,827  |  106,914  |
| Distance (km) | 450 |  827  |  |  633  |  1  |  3,214  |
| Tourism (dummy) | 450 | 0.30 |  | 0.459 | 0 | 1 |
| Mining (dummy) | 450 | 0.30 |  | 0.459 | 0 | 1 |
| International (dummy) | 450 | 0.04 |  | 0.196 | 0 | 1 |
| Exchange rate (index) | 450 |  96.22  |  |  8.79  |  86.30  |  109.80  |
| Commodity price (index) | 450 |  94.43  |  |  16.16  |  64.40  |  120.10  |
| Jet fuel (US$/gallon) | 450 |  2.39  |  |  0.55  |  1.66  |  3.06  |
| Fare index | 450 |  74.84  |  |  12.55  |  58.10  |  92.30  |
| Qantas Share | 450 |  0.49  |  |  0.38  | 0 | 1 |
| LCC Share | 450 |  0.21  |  |  0.31  | 0 | 1 |
| No. of destination | 450 | 4.48 |  | 4.41 | 1 | 28 |
| No. of airlines | 450 | 2.587 |  | 1.611 | 1 | 8 |
| Qantas (dummy) | 450 | 0.762 |  | 0.426 | 0 | 1 |
| Jetstar (dummy) | 450 | 0.224 |  | 0.418 | 0 | 1 |
| Virgin (dummy) | 450 | 0.407 |  | 0.492 | 0 | 1 |
| Others (number) | 450 | 1.138 |  | 0.989 | 0 | 5 |

**Table 4**

Estimation of the demand and flight frequency equations.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Demand equation | 2SLS FE |   | 2SLS RE |   |
| LnTraffic | Coef. | Std. Err. | Coef. | Std. Err. |
| LnFlight | 0.195 | 0.312 | 0.208 | 0.261 |
| LnPop | 0.885 | 0.583 | 0.267\*\*\* | 0.092 |
| LnIncome | 0.855\*\* | 0.390 | 1.655\*\*\* | 0.363 |
| LnDist |  |  | -0.006 | 0.036 |
| Tourism |  |   | 1.312\*\*\* | 0.261 |
| Mining |  |   | -2.702\*\* | 1.126 |
| International |  |   | 1.285\*\*\* | 0.284 |
| Exchangerate | 0.003 | 0.002 | -0.0007 | 0.002 |
| Tourism\*exchangerate | -0.010\*\*\* | 0.002 | -0.010\*\*\* | 0.002 |
| Lncommodity | 0.124 | 0.131 | 0.236 | 0.148 |
| Mining\*lncommodity | 0.563\*\*\* | 0.195 | 0.488\*\* | 0.221 |
| Lnfare | 0.336\*\*\* | 0.131 | 0.390\*\*\* | 0.129 |
| Qantas Share | 0.545\*\*\* | 0.075 | 0.627\*\*\* | 0.07 |
| LCC Share | 1.141\*\*\* | 0.238 | 1.567\*\*\* | 0.161 |
| NoDest | -0.020 | 0.023 | -0.0007 | 0.022 |
| LnYear | -0.041 | 0.072 | -0.140\*\* | 0.06 |
| Constant | 8.945 | 49.825 | -13.213\*\*\* | 3.115 |
| Frequency equation | 2sls FE |   | 2sls RE |  |
| LnFlight | Coef. | Std. Err. | Coef. | Std. Err. |
| LnTraffic | 1.076\*\*\* | 0.086 | 0.878\*\*\* | 0.040 |
| LnAircraftSize | -1.428\*\*\* | 0.218 | -1.030\*\*\* | 0.045 |
| LnIncome | -0.040 | 0.199 | 0.195\*\* | 0.085 |
| International |  |   | -0.448\*\*\* | 0.092 |
| Tourism |  |   | -0.029 | 0.034 |
| Mining |  |   |  0.010 | 0.046 |
| Lnjetfuel |  -0.018 | 0.037 | -0.011 | 0.032 |
| Lnfare | -0.117 | 0.081 | -0.051 | 0.062 |
| Qantas Share | -0.019 | 0.085 | -0.065\* | 0.038 |
| LCC Share |  0.118 | 0.148 | -0.048 | 0.076 |
| NoAirline | 0.008 | 0.011 | 0.023\*\* | 0.010 |
| NoDest | 0.018\*\* | 0.009 | 0.027\*\*\* | 0.004 |
| LnYear |  0.019 | 0.039 | -0.024 | 0.019 |
| Constant | 2.096 | 2.193 | 0.076 | 0.935 |
| No. of Obs | 450 |   | 450 |   |

\*\*\*significant at 1% ; \*\*significant at 5%; \*significant at 10%.

**Table 5**

Airport entry by major airlines in the sample regional airports during 2005 to 2013.

1. Jetstar vs. Virgin

|  |  |  |  |
| --- | --- | --- | --- |
|  **Virgin****Jetstar** | 0 | 1 | Total |
| 0 | 267 | 82 | 349 |
| 1 | 0 | 101 | 101 |
| Total | 267 | 183 | 450 |

1. Qantas vs. Jetstar

|  |  |  |  |
| --- | --- | --- | --- |
|  **Jetstar****Qantas** | 0 | 1 | Total |
| 0 | 89 | 18 | 107 |
| 1 | 260 | 83 | 343 |
| Total | 349 | 101 | 450 |

1. Qantas vs. Virgin

|  |  |  |  |
| --- | --- | --- | --- |
|  **Virgin****Qantas** | 0 | 1 | Total |
| 0 | 87 | 20 | 107 |
| 1 | 180 | 163 | 343 |
| Total | 267 | 183 | 450 |

Note: 0 stands for no service at the airport (no airport entry); 1 stands service at the airport

Source: compiled by authors using OAG data

**Table 6**

Probit estimation of major airlines’ entry patterns at regional airports (Qantas, Jetstar and Virgin).

1. Qantas

|  |  |  |  |
| --- | --- | --- | --- |
|  | 1-year lag  |  | 2-year lag |
|   | Coef. | Std. Err. |  | Coef. | Std. Err. |
| $$LnPop\_{it-1}$$ | 0.347\*\*\* | 0.094 | $lnPop\_{it-2}$  | 0.334\*\*\* | 0.101 |
| $$LnIncome\_{it-1}$$ | 3.924\*\*\* | 0.642 | $lnIncome\_{it-2}$  | 4.052\*\*\* | 0.716 |
| $$Tourism\_{i}$$ | 0.481\*\* | 0.191 | $Tourism\_{i}$  | 0.558\*\*\* | 0.204 |
| $$Mining\_{i}$$ | -0.043 | 0.247 | $Mining\_{i}$  | 0.134 | 0.265 |
| $$LnFare\_{it-1}$$ | -0.063 | 0.895 | $lnFare\_{it-2}$  | 0.389 | 0.967 |
| $$Virgin\_{it-1}$$ | 5.234 | 130.84 | $Virgin\_{it-2}$  |  5.193 | 114.181  |
| $$Jetstar\_{it-1}$$ | -5.035 | 130.84 | $Jetstar\_{it-2}$  |  -4.960 | 114.181  |
| $$Others\_{it-1}$$ | -0.174\* | 0.096 | $Others\_{it-2}$  | -0.178\* | 0.103 |
| $$LnYear\_{t}$$ | -0.917\*\*\* | 0.337 | $lnYear\_{t}$  | -0.814\* | 0.479 |
| $$Constant$$ | -43.175\*\*\* | 8.477 | $Constant$  | -46.352\*\*\* | 9.402 |
| No. of Obs | 400 |  | No. of Obs | 350 |  |
| LR Chi2 | 112.69 |  | LR Chi2 | 102.08 |  |
| Pseudo R2 | 0.257 |  | Pseudo R2 | 0.266 |  |

1. Jetstar

|  |  |  |  |
| --- | --- | --- | --- |
|  | 1-year lag  |  | 2-year lag |
|   | Coef. | Std. Err. |  | Coef. | Std. Err. |
| $$LnPop\_{it-1}$$ | 1.210\*\*\* | 0.240 | $lnPop\_{it-2}$  | 1.173\*\*\* | 0.166 |
| $$LnIncome\_{it-1}$$ | 3.748\*\*\* | 2.07 | $lnIncome\_{it-2}$  | 3.957\*\*\* | 0.990 |
| $$Tourism\_{i}$$ | 0.439\*\* | 0.192 | $Tourism\_{i}$  | 0.451\*\* | 0.206 |
| $$Mining\_{i}$$ | -1.642\*\*\* | 0.387 | $Mining\_{i}$  | -1.678\*\*\* | 0.416 |
| $$LnFare\_{it-1}$$ | 1.128 | 0.980 | $lnFare\_{it-2}$  | 1.025 | 1.037 |
| $$Qantas\_{it-1}$$ | -0.645\*\*\* | 0.244 | $Qantas\_{it-2}$  | -0.634\*\* | 0.261 |
| $$Others\_{it-1}$$ | 0.013 | 0.092 | $Others\_{it-2}$  | -0.006 | 0.099 |
| $$LnYear\_{t}$$ | -0.718\* | 0.383 | $lnYear\_{t}$  | -0.889\* | 0.535 |
| $$Constant$$ | -56.782\*\*\* | 11.684 | $Constant$  | -57.679\*\*\* | 12.855 |
| No. of Obs | 400 |  | No. of Obs | 350 |  |
| LR Chi2 | 112.69 |  | LR Chi2 | 123.33 |  |
| Pseudo R2 | 0.257 |  | Pseudo R2 | 0.332 |  |

(c) Virgin

|  |  |  |  |
| --- | --- | --- | --- |
|  | 1-year lag  |  | 2-year lag |
|   | Coef. | Std. Err. |  | Coef. | Std. Err. |
| $$LnPop\_{it-1}$$ | 0.687\*\*\* | 0.095 | $lnPop\_{it-2}$  | 0.628\*\*\* | 0.098 |
| $$LnIncome\_{it-1}$$ | 3.094\*\*\* | 0.648 | $lnIncome\_{it-2}$  | 2.832\*\*\* | 0.676 |
| $$Tourism\_{i}$$ | 0.466\*\*\* | 0.175 | $Tourism\_{i}$  | 0.476\*\*\* | 0.187 |
| $$Mining\_{i}$$ | -1.018\*\*\* | 0.283 | $Mining\_{i}$  | -0.816\*\*\* | 0.290 |
| $$LnFare\_{it-1}$$ | 0.847 | 0.828 | $lnFare\_{it-2}$  | 0.766 | 0.872 |
| $$Qantas\_{it-1}$$ | 0.341\* | 0.195 | $Qantas\_{it-2}$  | 0.433\*\* | 0.204 |
| $$Others\_{it-1}$$ | 0.100 | 0.085 | $Others\_{it-2}$  | 0.156\* | 0.093 |
| $$LnYear\_{t}$$ | 0.144 | 0.320 | $lnYear\_{t}$  | 0.281 | 0.440 |
| $$Constant$$ | -44.671\*\*\* | 8.558 | $Constant$  | -41.196\*\*\* | 8.985 |
| No. of Obs | 400 |  | No. of Obs | 350 |  |
| LR Chi2 | 147.86 |  | LR Chi2 | 124.68 |  |
| Pseudo R2 | 0.2720 |  | Pseudo R2 | 0.260 |  |

\*\*\*significant at 1% ; \*\*significant at 5%; \*significant at 10%.

 

(a)



(b)

**Fig. 1.** Distribution of average daily flight frequency at sample regional airports

\*Note: the vertical line is the Median; the curve is the fitted continuous density



(a)\*



(b)\*

\*Note: the vertical line is the Median; the curve is the fitted continuous density

**Fig. 2.** Distribution of average aircraft size at sample regional airports

Source: calculated from OAG data

**Fig. 3.** Average aircraft size of major airlines in the sample regional airport.

Source: Calculated from OAG data

**Fig. 4.** Share of total scheduled flights in the sample regional airports

**Appendix A**

**Table A1**

The 50 largest Australian regional airports included in the study.

|  |  |
| --- | --- |
| **Airport** | Airport Code |
| ALBURY | ABX |
| ALBANY | ALH |
| ARMIDALE | ARM |
| ALICE SPRINGS | ASP |
| AYERS ROCK | AYQ |
| BUNDABERG | BDB |
| BROKEN HILL | BHQ |
| BROOME | BME |
| BALLINA | BNK |
| BURNIE | BWT |
| COFFS HARBOUR | CFS |
| CAIRNS | CNS |
| DUBBO | DBO |
| DEVONPORT | DPO |
| DARWIN | DRW |
| EMERALD | EMD |
| GERALDTON | GET |
| GRIFFITH | GFF |
| GLADSTONE | GLT |
| GOVE | GOV |
| HOBART | HBA |
| THURSDAY ISLAND | HID |
| HAMILTON ISLAND | HTI |
| HERVEY BAY | HVB |
| MOUNT ISA | ISA |
| KALGOORLIE | KGI |
| KUNUNURRA | KNX |
| KARRATHA | KTA |
| LEARMONTH | LEA |
| LAUNCESTON | LST |
| MOUNT GAMBIER | MGB |
| MERIMBULA | MIM |
| MACKAY | MKY |
| MORANBAH | MOV |
| MILDURA | MQL |
| WILLIAMTOWN | NTL |
| OLYMPIC DAM | OLP |
| PARABURDOO | PBO |
| PORT HEDLAND | PHE |
| PORT LINCOLN | PLO |
| PROSERPINE | PPP |
| PORT MACQUARIE | PQQ |
| ROMA | RMA |
| ROCKHAMPTON | ROK |
| TAMWORTH | TMW |
| TOWNSVILLE | TSV |
| WHYALLA | WAY |
| WEIPA | WEI |
| WAGGA WAGGA | WGA |
| NEWMAN | ZNE |

**Appendix B**

Sargan-Hansen statistics to verify and select the instrumental variables for the 2SLS estimation.

We use the Sargan-Hansen statistics (Sargan, 1958) to verify the validity of our instrumental variables. The statistics for our estimation is as follows,

(A1) $J\_{nt}=nt \overbar{g}\_{nt}\left(\hat{φ}\right)^{'}\hat{Ω}\_{nt}^{-1}\overbar{g}\_{nt}\left(\hat{φ}\right)$

For equation (4.1) of the fixed effect (FE) model, we have

(A2) $\overbar{g}\_{nt}\left(\hat{φ}\right)=nt^{-1}\sum\_{i=1}^{N}\sum\_{t=1}^{T}( Z\_{2it}-\overbar{Z}\_{2it} )\left[( lnTraffic\_{it}-\overbar{lnTraffic\_{i}})-\hat{β}\_{1}(lnFlight\_{it}- \overbar{lnFlight\_{i}})+(X\_{1it}-\overbar{X}\_{1i})\hat{α}+(Z\_{1it}-\overbar{Z}\_{1i})\hat{δ}\right]$

where $\hat{Ω}\_{nt}$ is the estimator of the 2SLS weight matrix in the form of a GMM estimation, and $\hat{φ}$ is the estimator of the parameters $(\hat{β}\_{1},\hat{α}$**,**$ \hat{δ})$. Our aim is to verify the validity of the instrumental variables for the moment conditions $E(Z\_{2it}-\overbar{Z}\_{2it})(ε\_{1it}-\overbar{ε}\_{1i})=0$, where $Z\_{2it}=( lnjetfuel\_{t}, NoDest\_{it} )$.

The null hypothesis is $E(Z\_{2it}-\overbar{Z}\_{2it})(ε\_{1it}-\overbar{ε}\_{1i})=0$and the alternative hypothesis is $E(Z\_{2it}-\overbar{Z}\_{2it})(ε\_{1it}-\overbar{ε}\_{1i})\ne 0$. When the null hypothesis is true, the Sargan-Hansen statistics $J\_{nt}$ asymptotically follows a $χ^{2}$ distribution. We calculate the Sargan-Hansen statistics for equation (4.1) of the FE model, and the statistics value is 1.243, with a p-value of 0.2649, so we cannot reject the null hypothesis $E(Z\_{2it}-\overbar{Z}\_{2it})(ε\_{1it}-\overbar{ε}\_{1i})=0$. Thus, we conclude that $Z\_{2it}=(lnjetfuel\_{t}, NoDest\_{it} )$are valid instruments for the flight frequency in the demand function.

For equation (4.2), analogously we have

(A3) $\overbar{g}\_{nt}\left(\hat{φ}\right)=nt^{-1}\sum\_{i=1}^{N}\sum\_{t=1}^{T}(Z\_{1it}-\overbar{Z}\_{1it}) \left[β\_{2}(lnTraffic\_{it}-\overbar{lnTraffic\_{i}})+β\_{3}(lnAircraftsize\_{it}-\overbar{lnAircraftsize\_{i}}+(X\_{2it}-\overbar{X}\_{2it})ω+(Z\_{2it}-\overbar{Z}\_{2it})λ\right]$

From the equation system, the variables in $Z\_{1it}$**=**($lnPop\_{it}$, $lnDist\_{it}$, $Exchange\_{it}$, $Tourism\_{i}\*Exchange\_{it}$, and $Mining\*lnCommodity\_{it}$) might serve as instrumental variables. However, the null hypothesis of $E(Z\_{2it}-\overbar{Z}\_{2it})(ε\_{1it}-\overbar{ε}\_{1i})=0$ is rejected, with a statistics value of 22.637, and a p-value of 0.0001for the FE model. This indicates that not all of the variables in $Z\_{1it}$are valid instrumental variables for traffic demand and aircraft size.

Thus, we test the subset of$ Z\_{1it}$to find the valid instrumental variables. After testing the various subsets of $Z\_{1it}$, we find that $Z\_{3it}=(lnPop\_{it}$, $lnDist\_{it}$, $Exchange\_{it}$, $Tourism\_{i}\*Exchange\_{it})\in Z\_{1it}$can be valid instrumental variables for traffic demand and aircraft size, because we cannot reject $E(Z\_{3it}-\overbar{Z}\_{3it})(ε\_{1it}-\overbar{ε}\_{1i})=0$, with a statistics value of 2.598 and p-value of 0.2728.

**Appendix C**

**Table C1**

The first-stage regression results for the 2SLS fixed and random effects models.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Demand equation | FE |   | RE |   |
| LnFlight | Coef. | Std. Err. | Coef. | Std. Err. |
| *Lnjetfuel* | *0.123* | *0.119* | *0.100* | *0.118* |
| *NoAirline* | *0.049\*\*\** | *0.019* | *0.065\*\*\** | *0.019* |
| LnPop | 1.737\*\*\* | 0.300 | 0.292\*\*\* | 0.045 |
| LnIncome | 0.396 | 0.384 | 0.842\*\*\* | 0.244 |
| LnDist |  |  | -0.070\*\* | 0.034 |
| Tourism |  |   | -0.097 | 0.279 |
| Mining |  |   | -3.365\*\*\* | 0.623 |
| International |  |  | -0.499\* | 0.274 |
| exchangerate | 0.001 | 0.003  | 0.0003 | 0.003 |
| tourism\*exchangerate | -0.0003 | 0.003 | -0.00003 | 0.003 |
| Lncommodity | -0.342 | 0.209 | -0.382\* | 0.202 |
| Mining\*lncommodity | 0.458\*\*\* | 0.140 | 0.639\*\*\* | 0.138 |
| Lnfare | 0.110 | 0.182 | 0.115 | 0.179 |
| Qantas Share | 0.028 | 0.085 | 0.029 | 0.076 |
| LCC Share | 0.443 | 0.179 | 0.275\*\* | 0.133 |
| NoDest | 0.067\*\*\* | 0.008 | 0.070\*\*\* | 0.008 |
| LnYear | -0.096 | 0.068 | -0.083 | 0.058 |
| Constant | 10.204 | 56.492 | -2.322 | 3.604 |
| Frequency equation | FE |   | RE |  |
| LnTraffic | Coef. | Std. Err. | Coef. | Std. Err. |
| *LnPop* | *1.730\*\*\** | *0.297* | *0.375\*\*\** | *0.034* |
| *LnDist* | *-2.810* | *9.342* | *-0.017* | *0.050* |
| *Exchangerate* | *0.002* | *0.003* | *-0.001* | *0.003* |
| *Tourism\*exchangerate* | *-0.0136\*\*\** | *0.003* | *-0.014\*\*\** | *0.003* |
| LnIncome | 0.803\*\* | 0.346 | 1.725\*\*\* | 0.269 |
| Tourism |  |  | 1.692\*\*\* | 0.298 |
| Mining |  |  | -0.557\*\*\* | 0.180 |
| International |  |  | 1.211\*\*\* | 0.383 |
| Lnjetfuel | 0.103 | 0.076  | 0.073 | 0.080 |
| Lnfare | 0.269\* |  0.140 | 0.327\*\* | 0.145 |
| Qantas Share | 0.615\*\*\* | 0.089  | 0.661\*\*\* | 0.084 |
| LCC Share |  1.121\*\*\* | 0.188 | 1.436\*\*\* | 0.160 |
| NoAirline | 0.027 | 0.020 | 0.026 | 0.020 |
| NoDest | -0.002 | 0.009 | 0.008 | 0.009 |
| LnYear |  -0.015 | 0.049 | -0.071 | 0.047 |
| Constant | 1.891 | 58.602 | -12.122 | 3.123 |
| LnAircraftsize | Coef. | Std.Err | Coef | Std.Err |
| *LnPop* | *-0.048\*\*\** | *0.013* | *-0.003\*\*\** | *0.003* |
| *LnDist* |  |  | *0.030* | *0.024* |
| *Exchangerate* | *0.001* | *0.001* | *-0.001* | *0.002* |
| *Tourism\*exchangerate* | *-0.001* | *0.001* | *-0.008\*\*\** | *0.001* |
| LnIncome | 0.028 | 0.155 | 0.448\*\*\* | 0.129 |
| Tourism |  |  | 1.116 | 0.144 |
| Mining |  |  | 0.124 | 0.087 |
| International |  |  | 1.081\*\*\* | 0.184 |
| Lnjetfuel | 0.043 | 0.034 | 0.031 | 0.039 |
| Lnfare | -0.057 | 0.063 | -0.005 | 0.070 |
| Qantas Share |  0.413\*\*\* | 0.040 | 0.447\*\*\* | 0.041 |
| LCC Share | 0.653\*\*\* | 0.084 | 0.944\*\*\* | 0.077 |
| NoAirline | -0.013 | 0.009 | -0.023\*\* | 0.010 |
| NoDest | -0.037\*\*\* | 0.004 | -0.031\*\*\* | 0.004 |
| LnYear | 0.122\*\*\* | 0.022 | 0.067\*\*\* | 0.022 |
| Constant | -26.047 | 26.248 | -0.907 | 1.503 |
| No. of Obs | 450 |   | 450 |   |

\*\*\*significant at 1% ; \*\*significant at 5%; \*significant at 10%.

Note: the variables in “italics” are the instrumental variables.

**Appendix E**

**Table E1**

Estimation of the Demand and Flight Frequency Equations Using per Route Average Demand and Flight Frequency**.**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Demand equation | 2SLS FE |   | 2SLS RE |   |
| LnTraffic\_ave | Coef. | Std. Err. | Coef. | Std. Err. |
| LnFlight\_ave | 0.118 | 0.443 | -0.010 | 0.428 |
| LnPop | 1.473 | 1.032 | 0.340\*\* | 0.148 |
| LnIncome | 0.653 | 0.458 | 1.771\*\*\* | 0.500 |
| LnDist |  |  | 0.050 | 0.043 |
| Tourism |  |   | 1.423\*\*\* | 0.377 |
| Mining |  |   | -3.370\* | 1.761 |
| International |  |   | 2.993\*\*\* | 0.681 |
| Exchangerate | 0.004 | 0.003 | -0.0004 | 0.004 |
| Tourism\*exchangerate | -0.118\*\*\* | 0.003 | -0.0117\*\*\* | 0.004 |
| Lncommodity | 0.177 | 0.167 | 0.217 | 0.217 |
| Mining\*lncommodity | 0.500\*\* | 0.235 | 0.595\* | 0.340 |
| Lnfare | 0.380\*\* | 0.190 | 0.464\*\* | 0.198 |
| Qantas Share | 0.594\*\*\* | 0.107 | 0.703\*\*\* | 0.108 |
| LCC Share | 1.165\*\*\* | 0.323 | 1.630\*\*\* | 0.223 |
| NoDest | -0.199\*\*\* | 0.061 | -0.192\*\*\* | 0.056 |
| LnYear | -0.00001 | 0.084 | -0.104 | 0.076 |
| Constant | -29.900 | 72.303 | -14.422\*\*\* | 4.382 |
| Frequency equation | 2sls FE |   | 2sls RE |  |
| LnFlight\_ave | Coef. | Std. Err. | Coef. | Std. Err. |
| LnTraffic\_ave | 1.028\*\*\* | 0.059 | 0.855\*\*\* | 0.039 |
| LnAircraftSize | -1.145\*\*\* | 0.069 | -1.039\*\*\* | 0.038 |
| LnIncome | 0.052 | 0.160 | 0.199\*\* | 0.080 |
| International |  |   | -0.175 | 0.120 |
| Tourism |  |   | -0.019 | 0.031 |
| Mining |  |   |  -0.003 | 0.042 |
| Lnjetfuel |  -0.023 | 0.035 | -0.008 | 0.032 |
| Lnfare | -0.091 | 0.072 | -0.042 | 0.062 |
| Qantas Share | -0.110\*\* | 0.057 | -0.029 | 0.041 |
| LCC Share | -0.008 | 0.114 | -0.008 | 0.078 |
| NoAirline | 0.012 | 0.010 | 0.021\*\* | 0.009 |
| NoDest | 0.034\*\*\* | 0.012 | -0.002 | 0.007 |
| LnYear |  -0.020 | 0.025 | -0.013 | 0.019 |
| Constant | 0.473 | 1.704 | 0.224 | 0.882 |
| No. of Obs | 450 |   | 450 |   |

\*\*\*significant at 1% ; \*\*significant at 5%; \*significant at 10%.

**Appendix F**

**Table F1**

Alternative Probit model specification and estimation.

1. Qantas

|  |  |  |
| --- | --- | --- |
|  | RE probit model | Probit model (AR(1)) |
|  | Coef. | Std. Err. | Coef. | Std. Err. |
| $$LnPop\_{it-1}$$ | 0.922\*\*\* | 0.351 | 0.222 | 0.171 |
| $$LnIncome\_{it-1}$$ | 4.926\*\*\* | 1.764 | 0.611 | 0.472 |
| $$Tourism\_{i}$$ | 2.548\*\*\* | 0.943 | 0.487 | 0.453 |
| $$Mining\_{i}$$ | 1.901\* | 1.066 | 0.384 | 0.465 |
| $$LnFare\_{it-1}$$ | 0.359 | 1.541 | -0.455\* | 0.272 |
| $$Virgin\_{it-1}$$ | 19.620 | 1215.531 | 0.030 | 0.138 |
| $$Jetstar\_{it-1}$$ | -19.671 | 1215.531 | 0.054 | 0.278 |
| $$Others\_{it-1}$$ | -0.028 | 0.278 | 0.064 | 0.055 |
| $$Constant$$ | -62.117\*\* | 24.932 | -6.386 | 5.983 |
| No. of Obs | 400 |  | 400 |  |
| Wald chi-sq | 33.53 |  | 11.29 |  |
| Prob>chi2 | 0.000 |  | 0.187 |  |

1. Jetstar

|  |  |  |
| --- | --- | --- |
|  | RE probit model | Probit Model (AR(1)) |
|  | Coef. | Std. Err. | Coef. | Std. Err. |
| $$LnPop\_{it-1}$$ | 1.826\*\*\* | 0.479 | 1.141\*\*\* | 0.171 |
| $$LnIncome\_{it-1}$$ | 1.586 | 2.732 | 2.945\*\*\* | 0.747 |
| $$Tourism\_{i}$$ | 2.064\*\* | 0.912 | 0.418\*\* | 0.187 |
| $$Mining\_{i}$$ | -2.710 | 1.961 | -1.401\*\*\* | 0.351 |
| $$LnFare\_{it-1}$$ | 4.499\* | 2.482 | 2.369\*\*\* | 0.716 |
| $$Qantas\_{it-1}$$ | -0.399 | 0.965 | -0.549\*\* | 0.242 |
| $$Others\_{it-1}$$ | 0.073 | 0.359 | 0.055 | 0.088 |
| $$Constant$$ | -57.896 | 39.406 | -54.101\*\*\* | 11.275 |
| No. of Obs | 400 |  | 400 |  |
| Wald chi-sq | 31.070 |  | 73.51 |  |
| Prob>chi2 | 0.0001 |  | 0.0000 |  |

\*\*\*significant at 1% ; \*\*significant at 5%; \*significant at 10%.

(c). Virgin

|  |  |  |
| --- | --- | --- |
|  | RE probit model  |  Probit Model (AR(1)) |
|   | Coef. | Std. Err. | Coef. | Std. Err. |
| $$LnPop\_{it-1}$$ | 4.077\*\*\* | 1.104 | 0.821\*\*\* | 0.195 |
| $$LnIncome\_{it-1}$$ | 20.224\*\*\* | 5.184 | 3.739\*\*\* | 0.716 |
| $$Tourism\_{i}$$ | 5.561\* | 3.314 | 0.688\* | 0.382 |
| $$Mining\_{i}$$ | -3.366 | 2.226 | -0.861\* | 0.449 |
| $$LnFare\_{it-1}$$ | 4.754\*\* | 2.153 | 0.707\* | 0.436 |
| $$Qantas\_{it-1}$$ | -2.723\* | 1.501 | -0.254 | 0.243 |
| $$Others\_{it-1}$$ | -0.210 | 0.445 | -0.097 | 0.080 |
| $$Constant$$ | -278.960\*\*\* | 66.244 | -51.389\*\*\* | 9.588 |
| No. of Obs | 400 |  | 400 |  |
| Wald chi-sq | 34.18 |  | 36.44 |  |
| Prob>chi2 | 0.000 |  | 0.000 |  |

\*\*\*significant at 1% ; \*\*significant at 5%; \*significant at 10%.

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*E-mail address*: yahua.zhang@usq.edu.au (Y. Zhang). [↑](#footnote-ref-1)
2. Our sample only includes the top 50 regional airports because the government statistical reports only contain information on the top 50 regional airports. The passenger movements at the top 50 airports account for 95% of the total movements at all regional airports. [↑](#footnote-ref-2)
3. We also estimated the model without the fare index variable and the estimation results did not change significantly. Still, we cannot totally rule out the possible influence of endogeneity. We are thankful to an anonymous referee for raising this issue. [↑](#footnote-ref-3)
4. Variables with only subscript $i$ are time-invariant but airport specific variables, such as $Tourism\_{i}$, $Mining\_{i}$,$ International\_{i}$,$ and Dist\_{i}$. Variables with only subscript $t$ are time changing but not airport specific variables, such as $Fare\_{t}$, $Jetfuel\_{t}$.$ Exchange\_{t}$,$ and lnCommodity\_{t}$. [↑](#footnote-ref-4)
5. The first-stage regression on the endogenous variable for flight frequency,$ lnFlight\_{it}$, indicates that $NoAirline\_{it}$ is a strong instrument, while $lnJetfuel\_{t}$ may be weak. For the endogenous variables $lnTraffic\_{it}$ and $lnAircraft\_{it}$, the instrumental variables $lnPop\_{it}$ and $Tourism\_{i}\*Exchange\_{t}$ are strong instruments, while $lnDist\_{i}$ and $Exchange\_{t}$ are weak. However, Appendix 2 shows that all of the selected instrumental variables satisfy the exclusionary restrictions, so we keep all of the instruments. [↑](#footnote-ref-5)
6. In 2013, Virgin purchased a 60% share of Tiger Airways, another major LCC in Australia. In 2014, Tiger Airways became a fully owned LCC subsidiary of Virgin and changed its name to Tiger Australia. [↑](#footnote-ref-6)
7. It is possible that the airport effect $τ\_{i}$ is correlated with the explanatory variables, such that a fixed effects logit model can be used to deal with this potential endogeneity (note that fixed effects cannot be controlled for by the probit model due to the lack of a closed form cumulative density function to eliminate $τ\_{i}$ in the non-linear function). However, the fixed effects model is not suitable in this study for two reasons: (1) the airlines (Qantas, Jetstar, and Virgin) do not exhibit much variation in airport entry, thus providing insufficient power for an efficient logit model fixed effects estimation; and (2) The fixed effects model does not allow us to identify the coefficients of the time-invariant variables $Tourism\_{i}$ and $Mining\_{i}$. [↑](#footnote-ref-7)