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Entry effect of low-cost carriers on airport-pairs demand model using market concentration approach

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ABSTRACT

The trend of open sky policies and growth of low-cost airlines, the topic of airport-pairs demand is gradually being addressed in the golden aviation circle of Northeast Asia. The variety of flight services among the four major metropolises with dual-airport systems leads to a competition-cooperation relationship existing between various airports and airlines. Therefore, this study investigates the causal relationship between the route-level passenger demand and influential factors using aggregate data collected through website observations. The empirical study focuses on direct flights of airport-pair routes among Taipei, Shanghai, Seoul, and Tokyo. Results of the passenger regression model indicate that frequency, code-share, and morning flights have positive impacts on increasing passenger numbers for airlines. Further, the market concentration degree of Herfindahl-Hirschman Index and entry effect of low-cost carriers are important for the route-level passenger demand. In addition, routes with departures and arrivals in hub airports have a considerable attraction relative to other airport-pair routes. Finally, the proposed passenger model performs well in predicting market share, especially for routes with high demand.

1. Introduction

Trends such as open sky policies, low-cost airline growth, and airport financial autonomy accelerate airport competition in the golden aviation circle of Northeast Asia. This has accomplished the goal of single day travel cycle from Taiwan to Shanghai in China, Tokyo in Japan, and Seoul in the Republic of Korea. There are two important airports located in North Taiwan; Taoyuan International Airport (TPE), a large-scale hub airport with frequent flights; and Songshan International Airport (TSA), a city airport with access advantage to CBD. Similarly, the dual-airport system also exists in three destination cities, Shanghai (PVG and SHA airports), Tokyo (NRT and HND airports), and Seoul (ICN and SEL airports). Accordingly, passengers have varied options of airport-pairs routes for each city-pair flight. For example, with city-pairs flight from Taipei to Shanghai, one can choose among three airport-pairs routes: TPE-PVG, TSA-SHA, and TSA-PVG. Multiple airport-pairs routes lead to individuals facing diverse alternatives in air travel and intense competition among airlines. There also exist code-share (CS) flights among airlines. For example, considering the TPE-NRT route, there are CS flights operated by airlines of origin country (China Airlines, EVA Air, and TransAsia Airways), destination country (Japan Airlines and All Nippon Airways), third-party country (Cathay Pacific), and low cost carriers (Scoot and Vanilla Air).

In terms of entry effect of low cost carriers (LCC), most findings in previous research reveal that the entry effect of a LCC decreases the airfares and leads to an increase in the passenger traffic. The most famous case is the Southwest airlines effect; Goolsbee and Syverson (2008) revealed that the incumbents cut fares significantly when threatened by Southwest's entry. Fuellhart et al. (2013) indicated that the "Southwest effect" significantly explained the complexity of air-travel patterns within multiple-airport regions (MARs). Furthermore, the entry effect of LCC on airport competition and market structure has also been recognized by several studies (Fuellhart et al., 2013; Brueckner et al., 2014; Gillen and Hazledine, 2015). Murakami (2011) indicated that averagely, the type of airport, primary or secondary, does not affect the degree of airfare wars when LCCs enter market. Additional entries of LCCs do not affect the degree of airfare wars. Huma (2015) showed that the influence LCC used to exercise is diminishing in recent times. However, in terms of passenger traffic, entry has no direct effect, but indirectly through prices. In summary, most previous studies

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have addressed the effect of entry on LCC through airfare and passenger traffic, however, very few studies focus on entry effect through the influence of market concentration. Not only can this viewpoint be used to investigate airlines competition, but also examine the change of market structure after new LCCs' entries.

From the description of current aviation market, we can know that there exist competition-cooperation relationships between various airports and airlines. A passenger demand model with precise forecast is important to know what influential factors affect passenger demand and to help operating carriers propose a more effective strategy. Therefore, this study used aggregate data, instead of individual-level survey, to investigate the causal relationship between the route-level passenger demand and influential factors, such as flight attributes, airlines types, LCC effect, market power, and holiday factor. This study has three objectives:

1. Constructing a passenger demand model for airport-pairs routes;
2. Identifying those important factors and their effects on passenger demand; and
3. Validating the proposed passenger model with calibrating and validating samples.

2. Literature review

2.1. Dependent and explanatory variables

The units of observation for passenger demand include regions, airports, airlines, city-pairs, airport-pairs, and country-pairs. Since this study aims to investigate the competitions among airlines for direct flights within the Northeast Asia Golden Aviation Circle, we used the number of airlines passengers for airport-pairs routes as dependent variables. There are seven airport-pairs routes departing from TPE and TSA airports to three destination cities. In line with the time period of statistical data published by Civil Aeronautics Administration (CAA) of Taiwan, the total passengers flown monthly by airlines for a specific airport-pairs route was defined as the units of observation.

Regarding influential variables affecting passenger demand, seat supply, flight frequency, and connected cities are fundamental to defining international air passenger transport (Pacheco et al., 2015). Hsiao and Hansen (2011) indicated that airfare and flight frequency are the two most important variables in demand generation and assignment models. The other variables include travel time, schedule delay access time, and measures of attraction (e.g., destination city, population, or income). Furthermore, the level of concentration of air traffic has been addressed in recent studies (O'Connor, 2010; Van Nuffel et al., 2010; Pacheco et al., 2015). Hence, the market concentration approach was considered in this study to examine its impact on passenger demand and also used to examine the entry effect of new LCCs.

Numerous studies have proved that airfare is the most important variable affecting the demand of air passengers in aggregated demand model (Alderighi et al., 2015; Scotti and Dresner, 2015) and individual choice model (Wei and Hansen, 2005; Hsiao and Hansen, 2011). Those studies indicated that this variable has a negative and significant impact on passenger demand across varied units of observation. Except for the specification of airfare, Fuellhart et al. (2013) also adopted the low-fare share ratio to examine the marginal effect of LCC on passenger demand.

Thompson and Caves (1993), and Windle and Dresner (1995) used flight frequency to explore the choice behavior of individual travelers. They indicated that the higher the frequency, more willing were the travelers to choose alternatives of airlines or flights. Regarding the aggregated demand model, Wei and Hansen (2005, 2006) also obtained the same conclusion. These studies not only estimated the impact of flight frequency, but also showed that if an airline provides more morning flights, it will increase its market share with other airlines in the airport-pairs share model. In addition, Coldren et al. (2003) and Hsiao and Hansen (2011) both agreed that the punctuation of flights affected aviation demand. The results of their empirical studies indicated that the on-time performance of flights has a positive impact on the market share of airlines.

2.2. Market concentration index

This study focuses on the entry effect of new LCC using the degree of market concentration, the Herfindahl-Hirshman Index (HHI) (Hirschman, 1964). The method is originally used in income concentration studies and more recently have been used in air transport studies to investigate the competitive effect of market structure (Alderighi et al., 2015; Gillen and Hazledine, 2015; Pacheco et al., 2015; Scotti and Dresner, 2015). The HHI index provides an objective measure of market concentration, as in Equation (1), and equals to the sum of the squared share of seats for all the airlines operating on an airport-pairs route.

$$HHI = \sum_i \left(\frac{x_i}{\sum_i x_i} \right)^2 \tag{1}$$

where x_i can be the number of passengers, seats, and flights flown by airline i. The highest HHI value, 1, represents the monopolistic market. The lower value of HHI index means more carriers with similar shares of passengers/seats/flights compete in this air market.

In the case of a route with three airlines with equal market shares, the HHI would be 0.333. On the contrary, if a leading carrier with a market share of 0.8 competing with the other six carriers, the HHI index would be greater than 0.64. Thus, the index offers an object measure of the market concentration considering the number of carriers and their market shares simultaneously. Hence, this study used HHI index to investigate the effect of market competition on the number of passengers flown by airlines across all routes.

Furthermore, this study used the HHI index to propose a new index for measuring the entry effect of new LCCs. The index is only specified in the first few periods of new LCCs joining the market. The definition of *LccEntry* for period t is formulated as follows.

$$LccEntry_t(\%) = \frac{HHI_{t-1} - HHI_t}{HHI_{t-1}} \tag{2}$$

For convenience in explaining the definition of this new measure index, Table 1 listed the changes of HHI after the entry of a new LCC. Four new LCCs enter the market during our empirical data period. The month of new LCCs joining the market is defined as “Entry month ($t = 1$)” and the previous month of Entry is assumed to be the base period ($t = 0$). LccEnry is calculated with the HHI differences of two adjacent months by Equation (2). For example, when Scoot joined the TPE-NRT route, the LccEntry values of the 1st, 2nd, and 3rd month were 2.655%, 14.899%, and 7.411% respectively. As HHI is determined by the number of seats, the trend of HHI should be decreasing after new LCCs join market. Therefore, two periods with negative LccEntry values are not considered in our empirical data (both the 3rd month LccEntry value for Scoot's entry in TPE-ICN route and Vanilla Air's in TPE-NRT route). This is why the entry effects of new LCCs are only considered within the

Table 1
The changes of HHI after the entry of new LCC.

New LCC	Route	Variable	Entry			
			(t = 0)	(t = 1)	(t = 2)	(t = 3)
Scoot (Oct 2012)	TPE-NRT	HHI	0.30505	0.29695	0.25274	0.25390
		LccEntry	–	2.655%	14.899%	7.411%
Scoot (Jun 2013)	TPE-ICN	HHI	0.37087	0.33253	0.32034	0.32604
		LccEntry	–	10.338%	3.665%	–[a]
Spring (Dec 2013)	TPE-PVG	HHI	0.50796	0.40648	0.36129	0.37827
		LccEntry	–	19.977%	11.118%	–[a]
Vanilla Air (Dec 2013)	TPE-NRT	HHI	0.22880	0.21508	0.20541	0.19019
		LccEntry	–	5.997%	4.495%	7.411%

Note:
[a] LccEntry values are equal or close to zero.

first three months.

3. Data and methodology

The study focused on the direct flights departing from TPE and TSA airports to three metropolitan cities (Shanghai, Seoul, and Tokyo), which are located in the golden aviation circle of Northeast Asia. The operating flights include seven airport-pairs routes: TPE-PVG, TPE-ICN, TPE-NRT, TSA-SHA, TSA-PVG, TSA-HND, and TSA-SEL. The first three routes belong to the hub to hub (H2H) route, which means that both origin and destination airports are large-scale international airports with frequent flights and high numbers of air passengers. For systematic analysis, we grouped all airlines providing flight services above seven routes into five categories based on two issues concerning this study. One is focusing on the two major airlines in Taiwan and the other is how to measure the entry effect of the new LCCs. The categories are CI (China Airlines), BR (EVA Air), LCC1 (Scoot), LCC2 (Vanilla Air, Eastar Jet, T'way Air, and Spring airlines) and others (Cathay Pacific, Japan Airlines, TransAsia Airways, Shanghai Airlines, and so on). Data were collected from January 2012 to June 2015, a total of 42 periods. The samples in the first 39 periods were used for the passenger regression model and the others (April, May, and June 2015) were used as validating samples.

3.1. Data collection

As the CAA of Taiwan provides figures of monthly passengers flown by each airline in all flying routes under analysis, the dependent variable was defined as the number of passengers flown by airlines on specific routes. Apart from the number of passengers, CAA database also contains information such as flights frequency and punctuality. The departure times and operating carriers of flights were also collected from the websites of TPE and TSA airports. This information was used to calculate the ratios of morning flights (departing before 12:00 p.m.) and code-share. The departure times are used to reveal the advantage of morning flights, because these flights arrive at the destination city before noon. These would be mostly preferred by touring passengers because they still have a half of day to go about their touring activities. In addition, the latter variable captures the increasing effect of the number of passengers for those airlines with CS agreement. This study defined CS as "parallel operation" (Alderighi et al., 2015), which means both airlines operate on the route with their own aircraft and are also the operating or marketing carriers (e.g., CI and China Eastern Airlines on the route TPE-PVG; BR and ANA on the route TPE-NRT; CI and Korean Air on the route TPE-ICN, and so on.). As CS often involves carriers with usually a leading market share in their own countries of origin (e.g, CI and BR in Taiwan), CS may be beneficial to both carriers since they do not need to create and own sales network in the other carrier's country (Flores-Fillol and Moner-Colonques, 2007).

As there is no longitudinal database of airfare for Taiwan aviation market, the website-observation method was used to collect airfare information. The major data-collecting task was to observe and record a huge sample of airfares available across airlines and airport-pairs routes during the empirical period. The airfare information was based on the airlines and air ticket websites. These were recorded manually, over a period of eight weeks. For example, on a particular route, the airfares of the specific airline were collected two, four, six, and eight weeks in advance of the observation day, and airfare were collected on Monday and Friday for each observation week via airlines and air ticket websites.

3.2. Passenger regression model

The passenger regression model examines the effect of various independent variables on the number of passengers of airlines with airport-pairs for the period of 39 months. Explanatory variables in this model include airlines, destination, and time-related dummy variables; flight-related variables, market concentration variables, and entry effect for new LCCs. Below are the definitions of these variables:

1. *Pass* is the total number of passengers flown by airline *i* on route *r*, thousands of passengers per month.
2. *CI* and BR are dummy variables for two major airlines in Taiwan: China Airlines and EVA Air.
3. *LCC1* and *LCC2* are dummy variables for two kinds of low cost carriers. The former means the third-party carrier, for example, Scoot. In other words, the third-party LCC does not belong to origin or destination country. The latter indicates other LCCs such as Vanilla Air, Eastar Jet, T'way Air, and Spring airlines.
4. *H2H* is a dummy variable equal 1 if the departure and arrival airports of route *r* belong to hub airport.
5. *Summer* and *Winter* are dummy variables for vacation if the month is July/August and January/February.
6. *Tokyo* and *Seoul* are dummy variables if the destination cities of flight are Tokyo and Seoul respectively.
7. *Fare* is the average airfare for airline *i* on the route *r*, which was collected from air ticket website (Eztravel).
8. *LnFI* is the logarithm of number of flights by airline *i* on route *r*
9. *CS* indicates the ratio of code-share flights by airline *i* on route *r*.
10. *MF* is the ratio of morning flights by airline *i* on route *r*.

11. *PunTSA* is the punctuality of flight departing from TSA airport for airline *i* on route *r*.
12. *HHI* is the sum of the square of the seats shares for all the airlines operating on route *r*.
13. *LccEntry* is the sum of the HHI differences for the first three months after new LCC starts to operate on route *r*.
14. *LnAvePas* is the logarithm of average passengers of the previous three months for airline *i* on route *r*.

In summary, the passenger regression model were constructed and applied as follows. The monthly passenger demand of airline *i* for airport-pairs route *r* is formulated as Equation (3). The explanatory variables explained above, with their corresponding coefficients of $\beta_0 \sim \beta_{17}$, where β_0 is a constant.

$$\begin{aligned} Pass_{ir} = {} & \beta_0 + \beta_1 CI + \beta_2 BR + \beta_3 LCC1 + \beta_4 LCC2 + \beta_5 H2H \\ & + \beta_6 Tokyo + \beta_7 Seoul + \beta_8 Summer + \beta_9 Winter \\ & + \beta_{10} Fare + \beta_{11} LnFI + \beta_{12} CS + \beta_{13} MF + \beta_{14} PunTSA \\ & + \beta_{15} HHI + \beta_{16} LccEntry + \beta_{17} LnAvePas \end{aligned} \tag{3}$$

As any joining of new airlines, no matter FSC or LCC, will change the market structure, this study adopted the regression model with time series data (number of monthly passengers) to reveal the continuous effect of LCC operation (Wei and Hansen, 2006; Fuellhart et al., 2013; Brueckner et al., 2014). In addition, we also propose a new variable, *LccEntry*, to investigate the temporary effect of LCC entry. As this variable is defined from the HHI difference between two adjacent months (as Equation (2)), we can examine the temporary effect by specifying it on the first three months after LCC joining.

4. Empirical results

4.1. Descriptive statistics

Table 2 presents descriptive statistics for the variables in this empirical study. We consider seven routes in a period of 39 months and each route has two to seven operating carriers. A total of 881 observations were used to estimate the passenger regression model. The average airlines passengers are 12,390 per month, ranging from 155 to 43,220. The average round-trip fare is TWD 12,410 with flying distance between 419 and 1356 miles (1USD = 31TWD, 2015).

The average route frequency is about 57 flights per airline per month. The average CS ratio is 18.7% with a highest one of 57.1%. This means that one of every two flights belong to CS flight, especially for TSA-SHA and TSA-SEL airport-pairs routes. The reason could be the limits of airport capacity. This is because the origin and destination airports of the both foregoing routes are not hub airports. In addition, the average ratio of morning flights is 8.7%, in which the MF of CI (14.92%) is relatively higher than the other airlines since it is the flagship airline of Taiwan. The average value of HHI index is equal to 0.39, equivalent to less than three carriers with equal share of seats flown on an airport-pairs route. Moreover, the average LccEntry is 12.1% with a range of 0–19.9%. The maximum difference of LccEntry is high to about 20%.

Table 2
Descriptive statistics.

Variable	Type	Mean	Std. Dev.	Min	Max
Pass	thousands of pass.	12.39	9.92	0.155	43.22
CI	dummy	0.26	0.44	0	1
BR	dummy	0.26	0.44	0	1
LCC1	dummy	0.06	0.24	0	1
LCC2	dummy	0.07	0.26	0	1
Tokyo	dummy	0.34	0.47	0	1
Seoul	dummy	0.27	0.44	0	1
Summer	dummy	0.15	0.36	0	1
Winter	dummy	0.23	0.42	0	1
H2H	dummy	0.58	0.49	0	1
Fare	Thousands of NTD	12.41	2.86	1.09	19.50
LnFI	Ln (number of flights)	3.71	0.89	1.10	5.23
CS	ratio	18.7%	0.215	0	57.1%
MF	ratio	8.7%	0.077	0	25%
PunTSA	ratio	39.3%	0.463	0	100%
HHI	0–1	0.390	0.119	0.176	0.639
LnAvePas	Ln (average pass./1000)	3.555	0.897	0	4.49
LccEntry	Difference of HHI	12.1%	1.260	0	19.9%

4.2. Regression results

In the pilot estimation of passenger regression model, this study examines the correlations among those continuous flight variables (LnFI, CS, MF, and PunTSA). Most of those Pearson correlation coefficients are below 0.4, except for the correlation between LnFI and CS (0.661). Therefore, we further estimate a reduced regression model (reduced model), excluding CS from our regression model (full model), to investigate the explanatory power of CS. Although a moderate correlation exists between LnFI and CS, the result of partial F-test $\left(F = \frac{(79316.371 - 79279.332)/1}{7253.519/863} = 4.407 > F_{(5\%,1,\infty)} = 3.84 \right)$ shows that the adding of CS variable significantly increases the fitness of passenger regression model. Table 3 shows the results of the passenger regression model. The R-squared and adjusted R-squared are 0.916 and 0.915 respectively, and the F-test is also statistically significant with a significance level of 1%. In addition, all the coefficients (except LCC2) have the expected signs and are strongly significant. The results of the goodness-of-fit and significance level of the regression model indicate that it has the ability to

Table 3
Regression results for the passenger model.

Variables	Coefficient[a]	(Std. error)
Constant	-45.171^{***}	(2.378)
CI	6.355^{***}	(0.453)
BR	3.971^{***}	(0.373)
LCC1	2.355^{***}	(0.486)
LCC2	-0.751	(0.561)
Tokyo	3.296^{***}	(0.461)
Seoul	1.066^{***}	(0.340)
Summer	0.876^{***}	(0.280)
Winter	0.547^{**}	(0.241)
H2H	11.221^{***}	(2.135)
Fare	-0.198^{***}	(0.049)
LnFI	6.308^{***}	(0.246)
CS	2.001^{**}	(0.953)
MF	7.436^{***}	(1.982)
PunTSA	9.263^{***}	(2.249)
HHI	28.776^{***}	(1.835)
LnAvePas	2.773^{***}	(0.237)
LccEntry	0.224^{***}	(0.080)
Observations	881	
R-squared	0.916	
Adjusted R-squared	0.915	
Sum of squares regression (SSR)[b]	79316.371	
Sum of squares residuals (SSE)	7253.519	
F-statistic	555.106^{***}	
Durbin-Watson Statistic:	1.709	

Note:
[a] *,**and *** indicate significance at the 10%, 5% and 1% level, respectively.
[b] The SSR of the reduced model (excluding CS variable) is 79279.332.

establish a causal relationship between airlines passenger demand and the explanatory variables. In addition, as the Durbin Watson statistic is 1.709, no significant proof indicates that positive or negative autocorrelation exist in the residuals from the proposed regression model ($\alpha = 5\%$, $d_{L(17,881)} = 1.588$, $d_{U(17,881)} = 1.955$) . The result of regression model is listed in Table 3.

In terms of airlines, as expected, CI and BR have great positive impacts on passenger demand than the other airlines, because they are the two major airlines of Taiwan. Regarding the impacts of LCCs, the impact of LCC1 is positive and statistically significant while LCC2 has a negative impact. In the case of this study, LCC1 represent the third-party LCC carrier, Scoot Airlines, and LCC2 are those LCCs of destination countries. The result indicates that the well-known LCC has a greater positive impact than the regional LCCs. Regarding the impacts of destination and holiday, Tokyo and Seoul dummies with positive and significant impacts imply that the both cities attract more passengers than Shanghai, ceteris paribus. In addition, the Summer (July and August) and Winter (January and February) coefficients are also significant and indicate that these months generate more passenger demand than others. As the former is during school holidays and the latter is during the Lunar New Year in Taiwan, there are more overseas touring trips in these months.

The H2H coefficient is strongly significant and indicates that airlines flown on this kind of route has a huge impact on passenger demand. As these cities have two airports each to serve, the city-pairs flights and passengers can choose alternative routes to the destination city of their choice. The positive magnitude of H2H coefficient reveals that the route with arrivals and departures in hub airports has great impacts on passenger demand. The reason could be the convenience of frequent flights to hub airports that are usually located far away from the CBD of destination city. Regarding to airfare factor, three variable specifications were used to compare their explanatory power including logarithmic, linear, and square transformations. In addition, this study also adopted the average of all airfares observed from each point of time within eight weeks to relieve the influence of time change. After numerous pilot estimations, the result indicates that the average airfare with linear transformation has the best explanatory power than the other alternative specifications. As expected, the airfare has a negative effect on passenger demand with a coefficient of −0.198 implying that a 1% increase in fares produce a 0.198% decrease in passenger demand. Based on the mean passenger and fare of this study, a 1USD increase in fares will result in a loss about 6.13 passengers per month ($0.198 \times 12.39/12.41 \times 31$). It means that a 10% discount in average fare will cause an increase of 245 passengers per month. The other interesting variable is the number of flights. The LnFl coefficient is positive and statistically significant. Based on the average passengers and LnFl, a coefficient of 6.308 indicates that an increase in flight by one will cause an increase of 1913 passengers per month ($(6.308 \times 12.39 \times 1000/\exp(3.71))$).

Both ratios of CS and MF have positive coefficients and the impact of the latter is about 3.7 times greater than the former. It means that departure time is more important than the factor of code-share. Furthermore, the punctuality is only significant in the non-hub departure airport. The reason could be that although the hub airport has the advantage of frequent flights, the heavy air traffic also usually leads to the flight delay. According to the previous result, the non-hub airport has a higher performance in flight punctuality and therefore has a positive impact on passenger demand. In summary, from the coefficients of the flight-related variables above, the frequency and departure time have greater impacts on passenger demand relative to the airfare for this empirical study. The results could be based on two reasons. First, the demand of airport-pair air passenger exceeds the supply of flight services in the current aviation market. Second, the airfares among airlines may not compete intensively. Even more than five LCCs has joined the target market in the research period, the market share of all LCCs in total passenger volume is only 7.3%. The airfare of FSC alleviates the variation of LCC airfare.

With respect to the factor of market structure, the HHI coefficient is positive and statistically significant. For instance, if there are two cases of aviation market with equal shares of seats, with two and three carriers, respectively, the coefficient (28.776) is estimated to a difference of about 4806 passengers a month. Another interesting variable is LccEntry, which was specified from the changes in HHI when a new LCC enters the market. Generally, the HHI value will decrease when new carriers enter the current market. Since this study attempt to investigate the entry effect of a new LCC on passenger demand, this study adopted the LccEntry (defined as Subsection 2.2) to reveal the increase of passengers flown by the new LCC. Observing the trend of HHI changes, we found that the HHI of the fourth month after a new LCC joining the market is a turning point from a decreasing to an increasing HHI. Hence, this study selects the LccEntry values of first three periods to represent the entry effect of new LCC. The significant coefficient implies that the differences of HHI within first three months have positive impacts on passengers demand. Actually, the original equation specified three variables to represent the impacts of first, second, and third month, respectively. However, the preliminary result shows that there is no significant difference among these three variables. Therefore, for model simplification, we specified the same impact for the LccEntry variables of first three months. The significance of LccEntry coefficient reveals that the LCC entry has a positive impact on passenger traffic during the first three months. Comparing its magnitude to the coefficient of Fare, a ratio of −1.13 (0.224/(-0.198)) is obtained. This result is similar to the study of Goolsbee and Syverson (2008). They indicated that the impact of the quantity response (number of passengers) is about twice the changes in airfare, suggesting a demand elasticity of about −1. Finally, LnAvePas is used as the proxy of market size for a route. This study specified the logarithm of average passengers of the previous three months to catch the size effect of air passenger market across routes.

4.3. Validation

In order to examine the model validation, we used calibrating and validating samples to predict the number of monthly passengers. For convenience to compare the prediction performance across routes, we used the market shares of airlines instead of passengers demand. The criterion of route prediction is the sum of absolute percentage of prediction error (MAPE) for each airline, named as R-MAPE. Table 4 summarized the mean, max, min, and

Table 4
The R-MAPE for calibration sample.

R-MAPE (%)	TPE			TSA			
	ICN	NRT	PVG	SEL	HND	PVG	SHA
Average pass.	49,519	72,908	58,252	8,885	57,664	6,078	27,673
N of airlines	4	7	5	3	2	2	3
Mean	3.85	3.58	4.19	14.48	1.50	18.08	2.81
Max	8.03	5.45	10.35	24.43	2.83	58.66	6.64
Min	2.02	2.08	0.61	4.11	0.16	0.23	0.37
SD	1.65	0.87	2.25	7.66	0.68	15.54	1.69

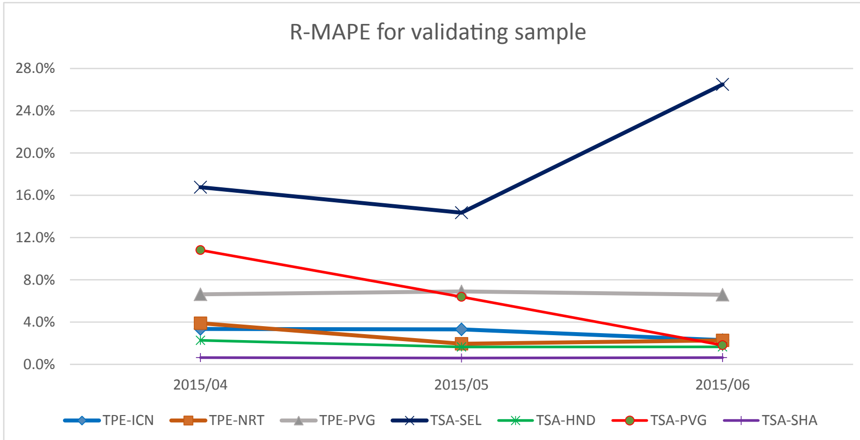

Fig. 1. The R-MAPE for validating sample.

standard deviation of R-MAPE among seven routes. Most of the routes have a great performance on R-MAPE, except for TSA-SEL and TSA-PVG. The best performance of prediction among routes is TSA-HND with a 1.5% of average R-MAPE, followed by TSA-SHA (2.81%), TPE-NRT (3.58%), TPE-ICN (3.85%), and TPE-PVG (4.19%). All these routes have a great amount of passengers demand, ranging from 27,673 to 72,908 per month. In contrast, the two routes with the highest R-MAPE mean, TSA-SEL (14.48%) and TSA-PVG (18.08%), have a passenger demand of less than 10,000 per month. The same trend can also be noted from the SD of R-MAPE. From the above results of prediction error we can conclude that the passenger regression model of this study have a better performance on calibration samples with a less than 5% of R-MAPE, especially for those routes with a great amount of passenger demand.

Another way to examine the prediction of passenger regression model is using the validation samples instead of calibration samples. This study reserved three periods of samples (April, May, and June in 2015) for model validation while calibrating the passenger regression. Fig. 1 illustrates the trend of the R-MAPE among seven routes. The trend of R-MAPE value across these routes is the same as the calibration samples. TSA-SHA, TSA-HND, TPE-NRT, and TPE-ICN routes have excellent and stable performance of prediction with a less than 4% R-MAPE across three periods. Although those R-MAPE of TPE-PVG in validating samples are slightly higher than the average value of calibration samples, their average value (7%) is still lower than the maximum of calibration samples (10.35%). Regarding the two routes with small amount of passengers, one interesting result is that the R-MAPE of TSA-PVG for three periods of validating samples (10.81%, 6.38% and 1.81%) are all lower than the average value of calibrating samples (18.08%) and the trend of its R-MAPE is even decreasing. The value of the last period of the validating sample is even low at 1.81% and almost equal to the prediction performance of TSA-HND. In addition, the R-MAPE of the first two periods of TSA-SEL route have a slightly higher than the average value of calibration samples. However, the value of last period is even higher at 26.5%, greater than the maximum of all calibrating samples. The reason for this particular outlier is that the Republic of Korea struggled against the MERS infection during May–July 2015. In June 2015, the total route passengers reduced to half and the number of flights flown by CI and BR reduced to 40% compared to that in May 2015. The dramatic changes in route passengers and number of flights lead to the significant bias of prediction by the passenger regression.

5. Conclusion

This study adopted a regression analysis method to construct the monthly demand model of airlines passengers for airport-pairs routes. As there no complete database for the aviation market, this study collects passenger demand and the influential variables via CAA statistics and the website-observation method. The main purpose is not only investigating the impacts of these variables, such as airfare, frequency, and airport capacity, but also examining the effects of market power and LCC entry. Furthermore, this study also validates the performance of model prediction by calibrating and validating samples. Several important results and insights are summarized below.

First, this study successfully constructed a passenger regression model within the constraint of scarce dataset in aviation demand and influential variables. Using the website-observation method, the results of regression model indicated that flight factor significantly affects the demand of airlines passengers through flight frequency, code-share flight, and the ratio of morning flight. Airfare and punctuality are another two influential flight factors, where the latter is only significant for non-hub departure airports. Another important insight is the significance of H2H variable. It implies that flights with departures and arrivals in hub airport have a strong positive impact on all airport-pair routes. It is observed that flights' frequency of origin and destination airports is still more effective than the factor of airport access. In addition, third-party LCCs receive more passenger demand than the LCCs of destination city owing to its reputation.

Second, this study also considered the factor of market structure including market concentration, entry effect, and market size. The HHI index, which is based on the number of seats flown by airlines, has a strong significance level and a high coefficient value. It indicated that the degree of market concentration by supply-side factor affects the passenger demand across airport-pairs routes. Although this finding reveals the trend of supply-oriented in our empirical market, the decision of airlines entry and flights change is still subject to the bilateral air services agreement among four targeted cities. The other important insight for this study is the measurement of entry effect for LCC. The result showed that while the new LCC enters a flight market of airport-pairs, the entry effect benefits the LCC passenger in the first three months.

Finally, the passenger regression model not only has a robust ability on fitness and significance, but also demonstrates a good performance on prediction in calibrating and validating samples. With the stable and decreasing trend on the R-MAPE, the result of external validation further reveals the good performance of the passenger regression model. Furthermore, in view of predicting performance across airport-pairs routes, the property of the regression analysis method reveals that those routes with high passenger demand performs precisely as predicted than that of those with fewer passengers. This result also points the direction of future research. As the size of observed samples is relatively small, there is no further possibility to segment all samples into sub samples. However, the causal relationship between passenger demand and influential variable in different size of aviation market could not be the same case, and it could be the reason why the prediction results are not the same trend across seven targeted airport-pairs routes. Hence, if future studies could collect more observed samples, we suggest sample segmentation based on market size or destination for a more comprehensive analysis.

In addition, two issues deserve further works to enhance the research method and empirical targets of our study. First, although the result of Durbin-Watson statistic does not prove the existence of first-order autocorrelation among residuals of passenger regression model, further study can adopt the time series analysis methods to examine the possibility of high-order autocorrelation. On the other hand, there are some most successful Asia markets for LCCs (e.g., TPE-KIX (Kansai International Airport) and TPE-OKA (Naha Airport)). The future study may use these target objects to examine the effect of LCC entry and test the validation of passenger regression model proposed by this study. The two issues can be suggested to the directions of future study.

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