

# **International Journal of Economic Research**

ISSN: 0972-9380

available at http: www.serialsjournal.com

© Serials Publications Pvt. Ltd.

Volume 14 • Number 6 • 2017

# **Determinants of Full-service Carriers Choices in Aviation Industry of Thailand**

# Anaspree Chaiwan<sup>1</sup> and Supanika Leucharusmee<sup>1</sup>

<sup>1</sup>Faculty of Economics, Chiang Mai University, Thailand.

Abstract: This study applied the classifier chain maximum entropy (CC-GME) method to examine factors determining consumers' choices of full-service carriers (FSCs) in Thailand's aviation market. The CC-GME method developed to explain multi-label choice behaviors is suitable for this study because each consumer generally chooses to travel with more than one carrier each year. The carrier choice determinants include not only consumers' demographics, but also consumers' scores on the importance of each carrier attribute toward their choices. The results show that consumers' demographics did not affect the carrier choices as much as the importance scores on carrier attributes. The carrier attribute with the highest impact was the airfares for Thai airways, Malaysia Airlines, and Bangkok Airways. In addition, the results also show that consumers who traveled with Thai Airways were more likely to also travel with Bangkok Airways and Malaysia Airlines than with other FSCs. The significance of the airfare indicates price competition and the dependence pattern of carrier choices indicates substitutability among FSCs.

#### INTRODUCTION

Competition in the ASEAN aviation market has changed drastically. From the overall international and domestic airline capacity in 2014, low-cost carriers (LCCs) are accounted for 61 percent in Philippines, 53 percent in Indonesia, 48 percent in Malaysia, 30 percent in Singapore, 29 percent in Thailand and 21 percent in Vietnam [Tan, 2014]. The fast growing market share of LCCs inflicts a higher level of competition on the full-service carriers (FSCs) [Pearson *et al.*, 2015]. In 2008, the ASEAN Air Transport Working Group initiated the ASEAN Single Aviation Market (ASEAN-SAM) to liberalize air travel between member countries lowing barriers for foreign carriers in the region to enter different markets. While the liberalization directly benefits travelers through more carrier choices with lower fares and indirectly benefits travel-related businesses [Tan, 2014], it brings a higher level and different pattern of competition in each local aviation market.

For Thailand, the two largest FSCs are Thai Airways and Bangkok Airways. From the Airports of Thailand (AOT)'s 2015 Traffic Report, Thai airways had the market share by passenger volume in Bangkok

(at the Suvarnabhumi and Donmueang airports) of 27.19 percent for international passengers and 12.57 percent for domestic passengers. Bangkok airways had a significantly smaller share for the international passengers of 2.16 percent, but only a slightly smaller share for the domestic passengers of 38.17 percent. Thai Airways was still the leader in the Thai aviation in both international and domestic market. Bangkok airways was ranked number six and two in the international and domestic market respectively. With the high growth rate of 21.31 percent in the demand for air transportation in Thailand, all airlines had a higher number of passengers, except for Thai Airways that had a negative growth rate in the domestic market. The FSCs in Thailand faces a higher competition in both international and domestic markets. For the international market, Thai FSCs faces competition from foreign FSCs. Thai Airways and Bangkok Airways only grew by 11.14 and 9.55 percent. However, China Eastern Airlines, China Southern Airlines and Hong Kong Airlines gained the international market share growth of 75.15, 58.64 and 37.14 percent respectively. For the domestic market, Thai FSCs faces competition from LCCs. Thai Airways had a negative growth of 17.57 percent and Bangkok Airways grew by 5.14 percent. Nok Air, the leading LCC in the international market with the market share of 29.32 percent, gained an increase in the market share of 11.91 percent. Thai Air Asia, Thai Lion Air and Thai Smile grew by 24.04, 157.27 and 187.46 percent respectively. A decline in the growth of Thai Airways' market shares resulted from an internal management and costs, includes a higher competition. However, the FSCs still have a strong positioning in terms of an airplane's sizes, route, and superior facilities and services. Skytrax World Airlines Awards voted by airline customers reported that Singapore Airlines achieved the third placed from the world's top 100 airlines in 2016, decreasing from the second placed in 2015. While, Thai Airways received an award "the World's Most Improve Airlines" and was the thirteenth placed in 2016, increasing from the nineteenth placed in 2015. Bangkok Airways was named as the Best Regional Airline in Asia and was the twentieth placed in 2016, increasing from the twenty-third placed in 2015. Malaysia Airlines was the thirty-fourth placed in 2016 decreasing from the twenty-fourth placed in 2015 [Skytrax, 2016].

Despite the high growth of demand, FSCs in Thailand need to prepare for the changes in the landscape of competition. Competitiveness can be improved through the supply and demand sides. For the supply side, carriers can improve efficiencies and reduce cost. For the demand side, carriers must study consumers' preferences to improve the competitiveness. Focusing only on the demand side, this study examines factors determining consumers' carrier choices of FSCs in Thailand's aviation market using the classifier chain maximum entropy (CC-GME) method.

This study examines two set of factors determining consumers' carrier choices. The first set includes the importance of each airlines' attributes and the second set includes consumers' characteristics. The criteria for the airlines' attributes is based on the key items related to the reliable international air transport rating organization "Skytrax" consisting of fares, passenger facilities and staff service, frequent flyer programs, aircraft types, terminal comfort and cleanliness, airline safety standards, and promotions. The magnitudes of the effects were estimated using the CC-GME model introduced by Leurcharusmee *et al.* (2015) for two separated reasons. The first reason addresses the contribution of the classifier chain (CC) part. The consumer choice for airlines is a multi-label choice, as oppose to single-labor choice, problem by nature. The single-label choice problem is well recognized in economics under the terms multiple choice or multinomial choice problem, where an individual chooses a choice from a choice set containing all available alternatives. The multi-label choice problem refers to the problem where an individual chooses more than one choice from the choice set. In the context of carrier choice, each of the consumers travels using more

than one carrier each year. Traditional econometrics models to estimate multi-label choice problem are extensions to logit and probit based multinomial choice models. Most commonly empirical studies for an individual choice use discrete choice models such as the Logit and Probit models to predict a set of alternatives e.g. the choice of transportation chooses, the choice of vehicle uses, the choice of purchases. Most commonly, each set of choices is treated as a choice in the model. The basic estimations of the binary choice models and applications are introduced in Jeliazkov and Rahman (2012). Milioti et al. (2015) also apply a multivariate choice model to investigate the attributes of the airline choices. This model can only predict the determinants of airline choices, not also a indicate dependence among the choices. This method of transforming multi-label problem into a single-label problem is inefficient when there present a large number of alternatives as the size of the choice set will increase rapidly. The CC method applies the Bayes' rule to decompose the probability of a consumer choosing a set of carriers into multiple binary choice models reducing the dimensions of the estimation significantly. In addition, logit and probit based models are parametric. Therefore, they are limited when the data do not have logistic or normal distribution. This leads to the second reason for using the Generalize Maximum Entropy (GME) to estimate parameters in the model. The GME model is a semi-parametric model and thus does not require an assumption on the error distribution. Moreover, the GME model is more robust with limited data [Golan et al., 1997].

This paper is organized as follows. A methodology is provided in section 2. Section 3 and 4 present the results, conclusions and remarks.

#### **METHODOLOGY**

This study apply the classifier chain generalized maximum entropy (CC-GME) model to analyze the effect of individual characteristics and key factors on an individual's decisions to use full service airlines. However, the result of comparison among choice models in Leucharusmee *et al.* (2015), the CC-GME model outperformed and had the lowest MSE.

## **Model Specification**

To predict an individual chooses among alternatives on the full service airlines, this study uses the classifier chain generalized maximum entropy model purposed by Leurcharusmee *et al.* (2015).

This model allow the correlation among alternatives. The estimation is the probability  $\Pr\{y_i = A | x_{ik}\}$  where  $y_i$  is the set of all alternatives that individual i choosing a set A and  $A \in 2^{\Omega}$ . The extension of the probability  $\Pr\{y_i = x_{ik}\}$  is as follows

$$\Pr\left\{y_{i} \middle| x_{ik}\right\} = \prod_{i=1}^{M} \Pr\left\{y_{ij} = 1 \middle| \tilde{x}_{ij}\right\} \tag{1}$$

And for the GME model in [], it would take the sequence of the choice  $y_{ij}$  for j = 1, ..., M by maximizing the total entropy.

To simplify the model, let the two alternatives in the choice set  $y_{ij} = \tilde{p}_{ij} + e_{ij}$ , the GME model is to maximize the entropy function as

$$\max_{\tilde{p},w} H\left(\tilde{p}_{ij}, w_{ijb}\right) = -\sum_{ij} \tilde{p}_{ij} \log\left(\tilde{p}_{ij}\right) - \sum_{ijb} w_{ijb} \log\left(w_{ijb}\right)$$
(2)

subject to

$$\sum_{i} \tilde{x}_{ijk_{j}} y_{ij} = \sum_{i} \tilde{x}_{ijk_{j}} \tilde{p}_{ij} + \sum_{ib} \tilde{x}_{ijk_{j}} v_{b} w_{ijb}, \ \forall j = 1, ..., M, \ \forall k_{j} = 1, ..., (k+j-1)$$
(3)

$$\sum_{b} w_{ijb} = 1, \ \forall i = 1, ..., N, \ \forall j = 1, ..., M$$
(4)

Equations (3) and (4) are the stochastic-moment and normalization constraints, respectively. To solve this maximization problem, the Lagrange function is used. For the detail is shown in Leurcharusmee *et al.* (2015).

To interpret the result, the effect of a change in an individual characteristics  $x_k$  is considered. This change is the marginal effects. For an individual who has a probability of an alternative  $j \in \Omega$ , the marginal effects is

$$\frac{\partial \Pr\left\{y_{j} \middle| \tilde{x}_{j}\right\}}{\partial x_{k}} = \beta_{jk} G'\left(\tilde{x}_{j} \beta_{j}\right)$$
(5)

For an individual who has a probability of a set of alternatives, the marginal effects is

$$\frac{\partial \Pr\left\{\underline{y}|x\right\}}{\partial x_k} = \sum_{j} \left[ \beta_{jk} G'\left(\tilde{x}_j \beta_j\right) \prod_{q \neq j} G\left(\tilde{x}_q \beta_q\right) \right]$$
(6)

# **Data Description**

The dataset is from the survey of airline passengers both arrival and depart from Bangkok, Thailand in 2016. Each respondent would choose what full service airlines he or she often use to travel as an dependent variable, namely,

1. Thai Airways,

2. Singapore Airlines,

3. Malaysia Airlines, and

4. Bangkok Airways.

The demographic data of an individual used as dummy variables include

1. female,

2. age above 30 years old,

3. marriage,

4. high education,

5. government officers,

6. high income (over a thousand dollars).

The study also employs affective airline's attributes as explanatory variables consisting with

8. fares,

9. ticket counter and service,

10. onbroad facilities,

11. flight reliability,

12. aircraft types,

12. check-in process,

- 13. cabin staff service,
- 14. promotions e.g. mileage, memberships, flyer bonus.

#### RESULTS

The average scores for the importance of each carriers' attributes are shown in Table 1

Table 1
Average scores from the carriers' respondents

		Average scores				
		Thai Airways	Singapore Airlines	Malaysia Airlines	Bangkok Airways	
No.	Attributes	$\mathcal{Y}_1$	$\mathcal{Y}_2$	$\mathcal{Y}_3$	$\mathcal{Y}_4$	Total
1.	Fares	4.34 [1]	4.39 [2]	4.44 [1]	4.40 [1]	4.39 [1]
2.	Ticket counter and service	3.97	4.22	3.72	4.08	4.00
3.	Onbroad facilities	3.97	4.29 [3]	4.17	3.91	4.09
4.	Flight reliability	4.26 [2]	4.27	3.94	4.32 [2]	4.20 [3]
5.	Aircraft types	4.09	4.07	4.33 [2]	4.05	4.14
6.	Check-in process	3.93	3.88	3.94	3.99	3.94
7.	Cabin staff service	4.19 [3]	4.49 [1]	4.33 [3]	4.30 [3]	4.33 [2]
8.	Promotions	4.05	4.20	3.78	4.08	4.03

<sup>&</sup>lt;sup>1</sup>Ranking in parentheses.

The scores shows that, for the overall airlines, the most importance of the carriers' attribute is fares, the second importance of those attributes is a cabin staff service and the third importance of the attributes is the flight reliability. Thai Airways has a same ranking for the importance of the carriers' attribute as Bangkok Airways from the most to the third importance of those attributes which are fares, flight reliability, and cabin staff service. However, the most importance of Singapore Airlines' attribute is cabin staff service.

The CC-GME model provide estimates of the parameters as shown in Table 2 as well as the parameters from Binary Logit model.

The parameters of the CC-GME model in Table 2 show that the significant consumer's characteristics for Thai Airways is government officers, and the significant airline's attributes are fares, aircraft types, and check-in process. The significant consumer's characteristics for Singapore Airlines is an above 30 years old consumer, and the significant airline's attributes are fares, onbroad facilities, flight reliability, check-in process, and cabin staff service. The significant consumer's characteristics for Malaysia Airlines is a marriage, and the significant airline's attributes are ticket counter and service, and flight reliability. Consumer's choice on Malaysia Airlines is also related to Thai Airways, and Singapore Airlines. The significant consumer's characteristics for Bangkok Airways is a female, and the significant airline's attribute is aircraft types. Consumer would also choose Bangkok Airways depending to Thai Airways.

Table 2
Estimated parameters for the CC-GME and Binary Logit models

Alternative	CC-GME	Binary Logit	Alternative	CC-GME	Binary Logit
y <sub>1</sub>			$\mathcal{Y}_2$		
Regressor			Regressor		
$\overline{x_1}$	0.043(0.245)	0.043(0.246)	$\mathcal{X}_{1}$	-0.527(0.376)	-0.647(0.403)
$\mathcal{X}_{2}$	0.178(0.324)	0.181(0.326)	$\mathcal{X}_{2}^{-}$	0.786(0.416)*	0.641(0.441)
$X_3$	-0.077(0.358)	-0.078(0.360)	$\mathcal{X}_{3}$	-0.572(0.481)	-0.702(0.505)
$\mathcal{X}_{4}$	0.476(0.327)	0.483(0.329)	$\mathcal{X}_{4}$	-0.299(0.474)	-0.303(0.498)
$x_{5}$	1.227(0.575)**	1.243(0.579)**	$\mathcal{X}_{\overline{5}}$	-0.490(0.579)	-1.111(0.833)
$x_6$	0.276(0.311)	0.279(0.313)	$x_6$	0.591(0.410)	0.554(0.545)
$a_{1}$	-0.394(0.146)**	-0.400(0.147)**	$a_{_1}$	-0.377(0.170)**	-0.341(0.184)*
$a_2$	-0.159(0.152)	-0.161(0.153)	$a_2$	0.286(0.223)	0.298(0.233)
$a_3$	0.197(0.139)	0.199(0.139)	$a_3$	0.360(0.213)*	0.352(0.227)
$a_4$	0.095(0.164)	0.096(0.165)	$a_4$	-0.424(0.231)*	-0.353(0.248)
$a_5$	0.296(0.150)**	0.300(0.151)**	$a_5$	-0.344(0.218)	-0.343(0.221)
$a_{6}$	-0.340(0.172)**	-0.345(0.173)**	$a_{6}$	-0.428(0.231)*	-0.465(0.239)**
$a_7$	0.033(0.172)	0.034(0.174)	$a_7$	0.444(0.253)*	0.566(0.270)**
$a_8$	0.175(0.122)	0.177(0.122)	$a_8^{'}$	-0.065(0.177)	-0.063(0.183)
8		,	${\cal Y}_1$	0.080(0.387)	_
AIC	1.201			0.677	
SIC	1.361			0.827	
$\overline{y_3}$			$\mathcal{Y}_4$		
Regressor			Regressor		
$X_1$	-0.629(0.606)	-0.973(0.713)	$\mathcal{X}_{1}$	-0.504(0.232)**	-0.517(0.229)**
$x_2$	0.685(0.633)	0.904(0.646)	$x_2^{}$	-0.298(0.298)	-0.133(0.290)
$X_3$	-1.864(0.943)**	-2.377(1.151)**	$\mathcal{X}_{3}$	-0.375(0.334)	-0.425(0.330)
$x_4$	-0.874(0.628)	$-1.177(0.674)^*$	$\mathcal{X}_{4}$	0.460(0.329)	0.507(0.323)
$x_5$	0.545(1.305)	0.314(1.458)	$x_5$	-0.200(0.540)	0.074(0.359)
$x_{6}$	0.968(0.766)	1.213(0.827)	$x_6$	0.367(0.297)	0.558(0.238)**
$a_1$	0.025(0.251)	0.059(0.262)	$a_{1}$	-0.176(0.123)	-0.210(0.118)*
$a_2$	-0.504(0.299)*	-0.526(0.317)*	$a_{2}^{\prime}$	0.122(0.137)	0.112(0.135)
$a_3$	0.092(0.299)	0.158(0.330)	$a_3$	-0.004(0.131)	0.052(0.128)
$a_4$	-0.626(0.319)**	-0.779(0.348)**	$a_4$	0.044(0.153)	0.005(0.148)
$a_{5}$	0.369(0.344)	0.274(0.369)	$a_{5}$	-0.266(0.143)*	-0.236(0.140)*
$a_6$	0.192(0.366)	0.248(0.398)	$a_6$	-0.090(0.153)	-0.125(0.150)
$a_7$	0.144(0.382)	0.244(0.409)	$a_{7}$	0.191(0.161)	0.2120.158
$a_7$ $a_8$	-0.320(0.239)	-0.383(0.250)	$a_7$ $a_8$	0.010(0.115)	0.008(0.114)
8	()	0.000(0.00)	8	(0.110)	Contd. table 2

Alternative	CC-GME	Binary Logit	Alternative	CC-GME	Binary Logit
$y_3$			${\cal Y}_4$		
Regressor Regressor					
$\overline{y_1}$	-0.858(0.517)*	_	$\mathcal{Y}_1$	0.439(0.246)*	_
$y_2$	1.177(0.664)*	_	$\mathcal{Y}_2$	0.543(0.370)	_
			$\mathcal{Y}_3$	0.810(0.529)	_
AIC	0.391			1.369	
SIC	0.581			1.569	

<sup>&</sup>lt;sup>1</sup>Standard errors in parentheses.

The marginal effects are shown in Table 3

Table 3
The marginal effects for the CC-GME model

Alternative		The marginal effects				
Regressor	$\mathcal{Y}_1$	${\cal Y}_2$	${\cal Y}_3$	$\mathcal{Y}_4$		
$X_1$	0.009	-0.038	-0.016	-0.119		
$x_2$	0.035	0.069	0.021	-0.071		
$x_3$	-0.015	-0.039	-0.033	-0.089		
$\mathcal{X}_{4}$	0.101	-0.025	-0.032	0.108		
$\mathcal{X}_{5}$	0.187	-0.032	0.018	-0.047		
$x_6$	0.055	0.045	0.026	0.088		
$a_1$	-0.078	-0.029	-0.001	-0.042		
$a_2$	-0.031	0.022	-0.014	0.030		
$a_3$	0.039	0.028	0.002	-0.001		
$a_4$	0.019	-0.033	-0.017	0.011		
$a_5$	0.059	-0.027	0.010	-0.064		
$a_6$	-0.067	-0.033	0.005	-0.022		
$a_7$	0.007	0.034	0.004	0.047		
$a_8$	0.035	-0.005	-0.009	0.002		
$\mathcal{Y}_1$	_	0.006	-0.028	0.104		
$\mathcal{Y}_2$	_	_	0.051	0.134		
$\mathcal{Y}_3$	_	_	_	0.199		

The implication of this finding is, for the example, the government officers would increasing to choose the Thai Airways with probability 0.19, the consumers who are age above 30 years old would increasing to choose Singapore Airlines with probability 0.19, the consumers who are married would decreasing to choose Malaysia Airlines with probability 0.04, and female consumers would decreasing to choose Bangkok Airlines with probability 0.12.

<sup>&</sup>lt;sup>2</sup>\*\* is 0.05 significant and \* is 0.10 significant.

Additionally, the results that getting from the CC–GME model can also provide the marginal effect of a dependence among carrier choices. Consumers who travel with Thai Airways tend to use Bangkok Airways with probability 0.20, but not use Malaysia Airlines with probability 0.03. Consumers who travel with Bangkok Airways are more likely to use Malaysia Airlines with probability 0.05.

#### **CONCLUDING REMARKS**

The results of the study show that consumers' demographics do not affect the carrier choices as much as important carriers' attributes. In addition, consumers choose different FSCs for different attributes of carriers indicating that each of the FSCs has a niche or potentially can develop a niche. Consumers choose Thai Airways for its low airfares, aircraft types, and check—in process. They choose Singapore Airlines for fares, onbroad facilities, flight reliability, check—in process, and cabin staff service. Consumers choose Malaysia Airlines for ticket counter and service, flight reliability and choose Bangkok Airways for aircraft types. Moreover, the results also indicate dependence pattern among all carrier choices. Specifically, consumers who travel with Thai Airways are more likely to also use Bangkok Airways, not use Malaysia Airlines. This dependence pattern indicate that some carriers are more likely to be substitutes among themselves.

## **REFERENCES**

- Golan, A., Judge, G., and Miller, D. (1997), Maximum entropy econometrics: Robust estimation with limited data.
- Jeliazkov, I., and Rahman, M. A. (2012), Binary and ordinal data analysis in economics: Modeling and estimation. *Mathematical modelling with multidisciplinary applications*, 123-150.
- Leurcharusmee, S., Sirisrisakulchai, J., Sriboonchitta, S., and Denœux, T. (2015), The classifier chain generalized maximum entropy model for multi-label choice problems. In *Econometrics of Risk* (pp. 185-199). Springer International Publishing.
- Milioti, C. P., Karlaftis, M. G., and Akkogiounoglou, E. (2015), Traveler perceptions and airline choice: A multivariate probit approach. *Journal of Air Transport Management*, 49, 46-52.
- Pearson, J., O'Connell, J. F., Pitfield, D., and Ryley, T. (2015), The strategic capability of Asian network airlines to compete with low-cost carriers. *Journal of Air Transport Management*, 47, 1-10.
- Tan, A. K. J. (2014), The ASEAN Single Aviation Market: Liberalizing the Airline Industry. ERIA Policy Brief. Jakarta: ERIA.