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Advance purchase behaviors of air tickets

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The advance purchase behaviors of air passengers are essential to develop revenue management strategies of airlines, which should be carefully studied. Based on this, this study aims to empirically investigate the advance purchase behaviors for airline tickets based on the airline transaction data of Taipei-Macau (TPEMFM) route in 2011. In order to model the advance purchase behaviors, multinomial logit models are used. To facilitate model development, the advance purchase horizon is divided into five time periods by three segmentation methods, including equal time periods, time periods with equal number of purchases and time periods according to professional judgment. Several factors contributing to advance purchase behaviors are examined, including price, flight schedule (time of day, day of week, and months of year) and fare class preferences. The estimation results show that the model with segmentation of equal time periods performs best in terms of adjusted rho-square and AIC indices. It is also found that air passengers tend to purchase tickets earlier for the flights in the morning and in hot season, suggesting the fare and seat inventory control should be varied for different flights.

1. Introduction

The principle of revenue management (RM) in the airline industry is to maximize their farebox revenue through pricing and allocating available seats under uncertain demand and perishable supply. In practice, RM implementation is usually associated with setting booking limits through different fare products. The booking limits restrain the maximum number of seats available for sale to a given booking class, whereas a fare product is a combination of a price and fare restrictions. Through setting the booking limits for each designed fare products, airlines are able to derive the optimal selling strategy based on remaining capacity, market conditions and anticipated demand.

Generally, RM demand model has been proposed based on a hypothesized inverse demand function using traditional statistics techniques, such as time series, averaging methods, or simple probability distributions (McGill and van Ryzin, 1999). Those demand models mostly assume passenger demand to be independent among fare products that created based on different restrictions for passenger segmentation. However, with increasing market competition from low cost carriers (LCCs) and the growth of online ticket sales, passengers nowadays may perceive fare classes as nothing more than different prices for a seat and purchase based on price rather than fare product. That results in the RM demand forecast model assumptions, such as independence across fare products, may no longer be valid (Barnhart and Smith, 2012). Additionally, airlines employ strikingly different pricing strategies under intense market competition, differentiated demand patterns, and achieving effective customer segmentation (Bilotkach et al., 2010). For example, by setting advance purchase discount, airlines are able to induce price-sensitive passengers to purchase earlier whereas the less price-sensitive but time-sensitive passengers purchase later and further shift demand (Gallego et al., 2008; Dana, 1999, 1998; Gale and Holmes, 1993). Moreover, airlines also adjust prices dynamically based on learning demand (Escobari, 2012; Deneckere and Peck, 2012). Passengers can decide to make advance purchase at the going price or to delay their purchase decision. Those price strategies may decrease the product value that passengers are forced to make trade-offs between price, product attributes and advance purchase deadlines, and therefore, change their purchasing behaviors (Hotle et al., 2015; Escobari, 2014). Without knowing the real purchasing behaviors of air passengers, the hypothesized demand function may lead to an erroneous estimated result.

In order to trace individuals' advance purchase decisions, recent researches have introduced discrete choice models to RM for its ability to accommodate passenger preferences in RM strategies that

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can better explain how individuals making trade-offs (Garrow, 2009; Talluri and van Ryzin, 2004a, 2004b). The decision of passengers can be modeled based on either stated preferences survey data (Proussaloglou and Koppelman, 1999; Wen and Lai, 2010) or revealed preferences data. Despite that demand models based on discrete choice models may be more appropriate in RM applications, for the revealed preferences settings, there is limited empirical research due to data acquisition problems. Both chosen and non-chosen alternatives are needed for revealed preference model implementations. Although the support of computer systems lowers down data collection costs, most of firms can still only record the results of passengers of successful purchase and information about non-chosen alternatives had been difficult to obtain, which made inferring the true demand with available data remains a quite expensive and challenge issue. Previous researches estimated logit models of demand to analyze advance purchase behaviors based on revealed preferences data in airline industry (Escobari and Mellado, 2014; Vulcano et al., 2010; Carrier, 2008), hotel (Newman et al., 2014) and railway industry (Hetrakul and Cirillo, 2013, 2014, 2015). To our best knowledge, Escobari and Mellado (2014) is the first study that using seat inventory changes and posted prices to estimate the flight itinerary choice from revealed preference approach, where both chosen and non-chosen information for all alternative flights of different airlines are available.

As mentioned above, this paper uses real transaction data from billing and settlement plan (BSP) which can be easily acquired by every airline to support the development of airline RM strategies. The remainder of this paper is organized as follows. Section 2 introduces the study data and methods used for model development. Sections 3 and 4 describe the model specifications and estimation results, respectively. Finally, the last section gives concluding remarks and suggests future research directions.

2. Data

The dataset used to investigate the potential contributing factors for advance purchase behaviors is the airline sale transaction data for its availability. The dataset is based on International Air Transport Association (IATA) billing and settlement plan (BSP) and widely used by every financial department of IATA members. The dataset contains every sale transaction records between airlines and diverse distribution channels, such as travel agencies, direct Internet sales and airline counters. Table 1 presents a sample record of airline revenue accounting data, the fields related to this study are ticket number, flight origin and destination, departure date, flight number, issued date (purchasing date), service class and price. As shown in Table 1, each record from airline sale transaction data has a unique ticket number and different flight coupons for the itinerary. The other interesting fields are service class and fare basis code as reported in Table 2 which represents different fare products and rules for numerous distribution channels and passenger value segments.

This study chooses Taipei-Macau (TPEMFM) route for its popularity and high flight frequencies. The flight length from Taipei to Macau is approximately 840 km and the flight time is about 2 h. Notably, the Taipei-Macau route has annual largest passengers in Taiwan (Taiwan Civil Aeronautics Administration, 2011). Fig. 1 shows the total passengers arranged by months, which illustrates that the most popular months flying to Macau were July and August, whereas March and October had the fewest passengers.

With the purposes to complete the purchasing information, the flight schedule data was integrated to the analysis dataset. The study airline offered 3 daily flights that departure in the morning, afternoon and evening (Departure at 08:10, 13:30 and 18:20; arrival at 09:45, 15:10, and 20:10, respectively). By combining two dataset, the departure time preferences of passengers such as time of day, days of week and months of year are then studied. Additionally, to study the time of advance purchase behaviors of air passengers, the advance purchase days was defined as days between ticket issued date and departure date. Fig. 2 depicts the number of tickets by advance purchase days prior to departure. Since almost all air passengers (97%) purchased their tickets within 60 days prior to departure, a horizon of a total of 60 days is studied. Table 3 presents the cumulative percentage of passengers within 7 advance purchase days, where about 2% of passengers purchased tickets at the departure day and almost 50% of passengers purchased tickets about one week prior to departure.

Fig. 3 further presents the average price distribution for defined class segmentations by the number of advance purchase days of Taipei-Macau route. Note that the business class has the highest average price and larger price dispersion whereas the package and group classes have the lowest average price. Compared with other classes, economic and package class are relatively stable within 60 days prior to departure. The average price of economic class was gradually decreasing in the beginning and the rising steadily around 25 days as the departure day approaches. The same pricing pattern can be also observed in other service classes. Based on the price variation over the sales horizon, passengers are assumed to make advance purchase decision based on ticket price and their flight time preferences.

While service class and fare basis are typically used for designing fare products, it is difficult to be applied in the study because of the complexity of various fare rules. Additionally, the BSP dataset contains not only transaction records from direct purchasing passengers but also from multiple distribution channels, which makes it hard to distinguish passengers' behaviors from travel agents. Therefore, for simplicity, this study considers only the

Table 1
A sample of air ticket transaction accounting data.

Column	Value
Departure Date	2011/12/1
Origin/Destination	TPEMFM
Fight Number	351
Coupon Number	1
Ticket Number	2440792555
Issue Station	TPE
Issue Date	2011/11/11
Sales Office	22473
Tour Code	403XIN2I162554
Fare Basis	[a]YEE3M/IN90
Service Class	K
Agent Code	34305585
Price (TWD)	2500

[a] YEE3M/IN90: Economy exclusion fare, valid 90 days for Infants.

Table 2
Descriptions of frequently used service class.

Service class code	Identifies
C, J	Business class
Y, W, B, V, Q, L, T, X	Economy class
G	Group Passengers
K, M	Package
D, S	Discount Fares
Fare-basis Code	**Identifies**
Y	Maximum stay of one year
YEE1M	Excursion fare, valid 30 days
YEE3M	Excursion fare, valid 90 days

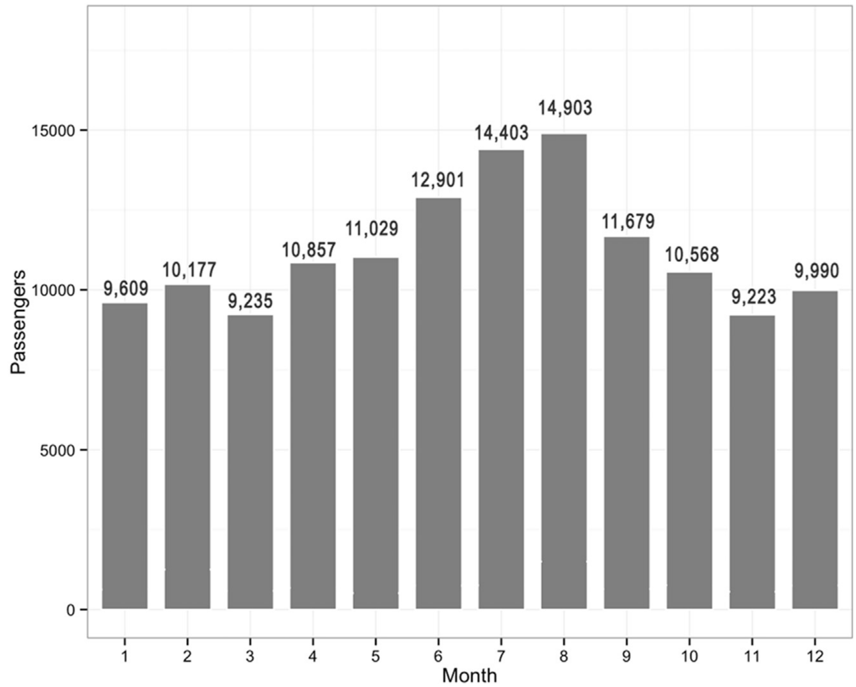

Fig. 1. Monthly number of passengers of TPEMFM.

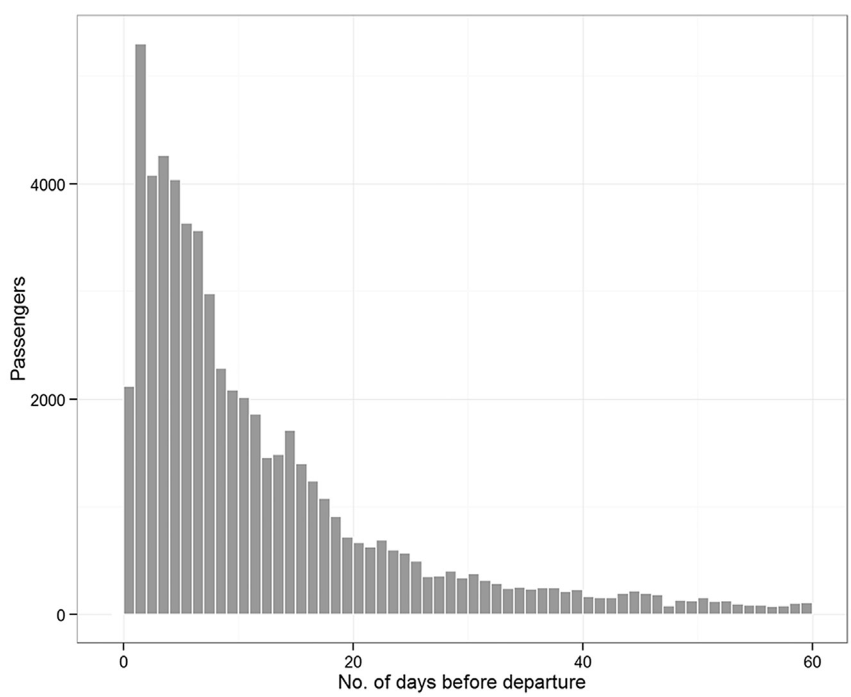

Fig. 2. Total number of advance purchases prior to departure.

subset of economic class (service classes of W, L, B, T, Q, X) of fare basis YEE3M tickets which been purchased through the direct purchasing channel (website and airline counters). Data anomalies including outliers or incomplete records were also removed, which results in the final of 2899 transaction records. Table 4 lists service classes selected for this study, whereas Fig. 4 presents the average price patterns of selected records.

3. Model

To investigate the advance purchase behaviors of air tickets, discrete choice models are used. Additionally, to reduce the number of alternatives and facilitate model development, the advance purchase horizon is divided into five time periods according to three segmentation methods: the first method is to divide the horizon into five equal time periods (each period is of 12 days). The

Table 3
Cumulative percentage of advance purchase passengers of last week.

Advance purchase days	Passengers	Percentage	Cumulative percentage
0	2478	1.84%	1.84%
1	9558	7.10%	8.94%
2	10637	7.90%	16.85%
3	7920	5.89%	22.73%
4	8660	6.44%	29.17%
5	8887	6.60%	35.77%
6	9201	6.84%	42.61%
7	9557	7.10%	49.71%

Table 4
Selected service classes.

Service classes	Avg. price	SD. price	Number	Percentage
W	4721.77	112.31	31	1.07%
L	4596.57	175.27	131	4.52%
B	4518.97	48.94	29	1.00%
T	3892.74	114.33	317	10.93%
Q	3788.71	36.69	62	2.14%
X	3404.99	122.14	2329	80.34%
Total/Average	3545.60	345.71	2899	100.00%

second method is to divide the horizon into five time periods with equal number of purchases. The third method is to divide the horizon according to professional judgment of the study airline.

For the professional judgment method that suggested by experts from the study airline, as departure day approaches, the airline will generally begin to check the seat reservations and decide to have discounts and promotions to raise sale volume or not. The airline will announce promotion information to travel agencies around 1–2 months from the departure day. Two weeks prior to departure, they will start to ask travel agencies to pay for group passengers, or return the remaining seats, so the remaining seats of the flight will change dramatically. In the last week prior to departure, promotions such as "last minute sale" and internet advertisements will be performed to attract individual passengers. Finally, we expect passengers purchasing tickets at the departure day have different choice behaviors.

This paper models the advance purchase behaviors in static settings and from airline perspective; hence we assume that all five purchasing period alternatives are available to passengers at the same time under perfect information. Additionally, since our data contains transactions data of only one carrier, it is not able to account for the choices of other flights or carriers. The settings here only consider the choice of advance purchase period within the same flight. Table 5 outlines the defined advance purchase time periods and number of passengers, whereas Fig. 5 demonstrates the relationships between defined periods and advance purchase days for the selected dataset.

However, for transaction data, only the time period of successful transaction was recorded and none of information regarding unsuccessful transactions in other time periods was available. A data-intensive method is used to impute the values of generic variables of other time periods. The purchase prices in the other periods of flight i were imputed by advance purchase days, service classes and purchase months. Passengers are assumed to be myopic that they purchase at the price whenever their valuation exceeds it. Finally, factors including price, and travel time preferences (time of day, day of week, and months of year) are then further examined by using multinomial logit (MNL) model.

As presented in Eq. (1), the utility of passenger n who purchased at the alternative advance purchase period i for flight j is given by,

$$U_{nij} = \alpha_{nij} + \beta \log(PRICE)_{nij} + \gamma \log(PRICE)_{nij} \times x_{nj} + \delta x_{nj} + \varepsilon_{nij} \quad (1)$$

The systematic component part of utility is modeled a linear function of observed characteristics, $V_{nij} = \alpha_{nij} + \beta \log(PRICE)_{nij} + \gamma \log(PRICE)_{nij} \times x_{nj} + \delta x_{nj}$, whereas the unobserved random component is expressed as ε_{nij}. β, γ and δ are the coefficients to be estimated.

In Eq. (1), α_{nij} is the alternative specific constant for the alternative i, $i \in Cn \in \{1, \ldots, 5\}$ which captures the average effect on utility of all variables that are not included in the model. The $\log(PRICE)_{nij}$ and its interaction terms of travel time preferences are settled as *generic variables*, that the marginal effect of the variable is assumed to have same impact on the utility of each alternative. The interaction term specification is helpful to account for the relationships between purchase price and flight preferences. Notably,

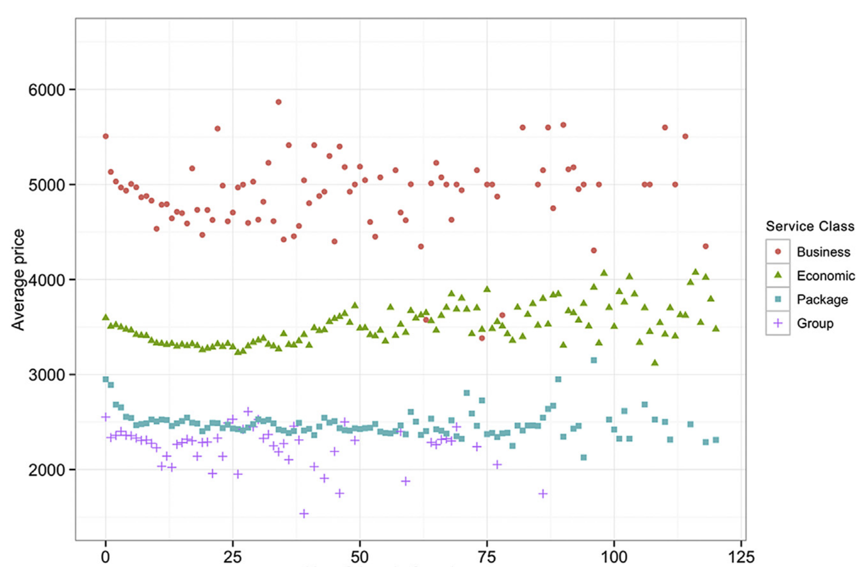

Fig. 3. Price distribution of various classes.

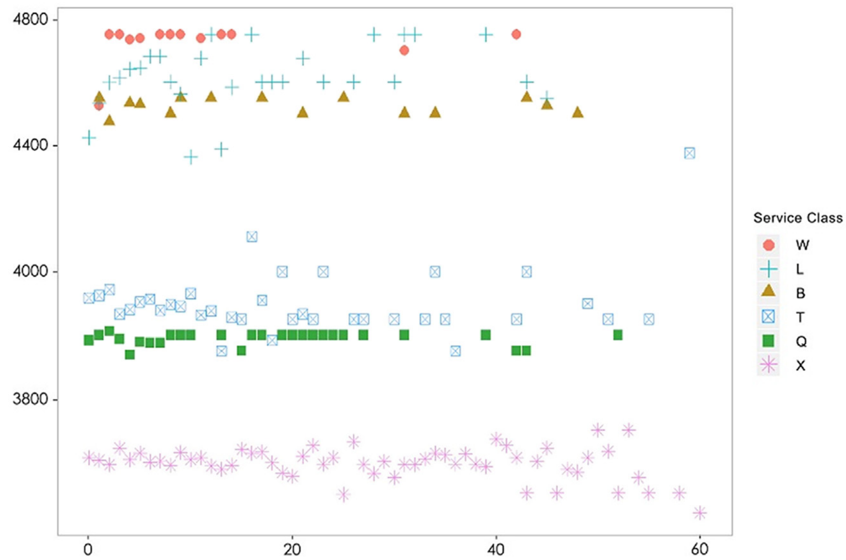

Fig. 4. Price distribution of economic class.

Table 5
Defined advance purchase periods.

Period	Equal time period		Equal purchase number		Professional judgement	
	Number	Days before Dep.	Number	Days before Dep.	Number	Days before Dep.
P1	2048 (71%)	0–12	744 (26%)	0–2	164 (6%)	0
P2	509 (18%)	13–24	676 (23%)	3–5	1396 (48%)	1–7
P3	204 (7%)	25–36	405 (14%)	6–9	632 (22%)	8–14
P4	105 (4%)	37–48	559 (19%)	10–17	497 (17%)	15–31
P5	33 (1%)	>49	515 (18%)	>17	210 (7%)	>31

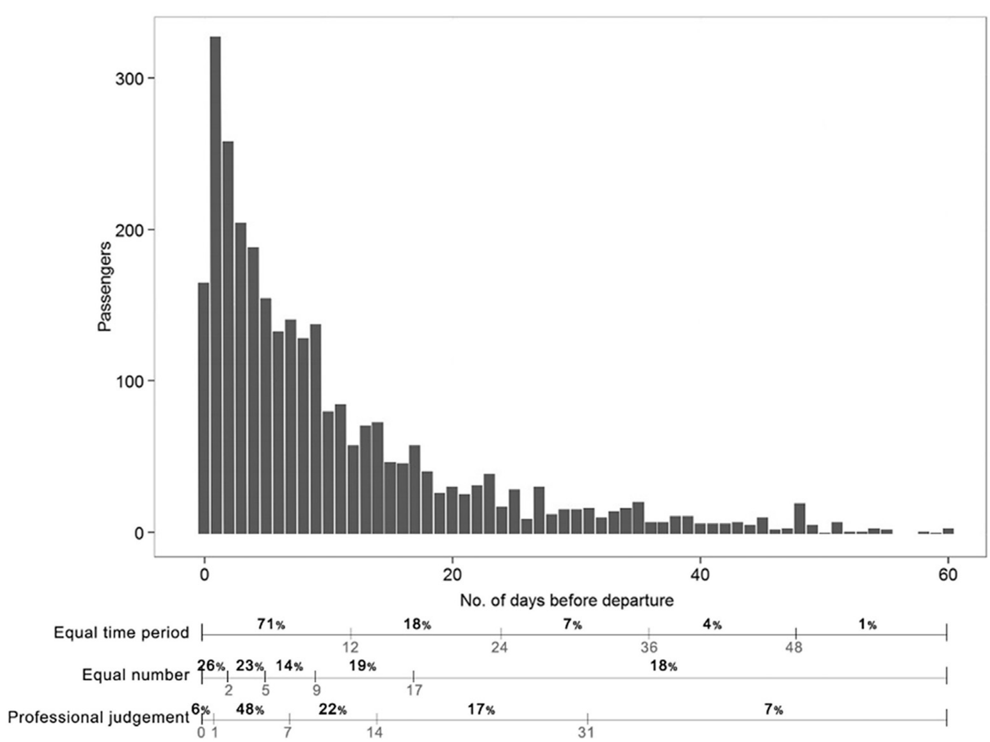

Fig. 5. Time periods of advance purchase of three segmentation methods.

if the carrier learns more about the demand as departure day approaches and dynamically adjust price strategies, the correlation between $\log(PRICE)_{nij}$ and the unobserved $x_{nj} + \varepsilon_{nij}$ may cause potential price endogeneity problem. Escobari (2012, 2014) controlled for the potential endogeneity with internal instruments and flight fixed effect. Since the price dynamic is not the current issue of this study, we assume ε_{nij} is uncorrelated with $\log(PRICE)_{nij}$. Finally, the probability P_{nij} of passenger n choosing advance purchase period i can be derived as Eq. (2).

$$P_{nij} = \frac{e^{V_{nij}}}{\sum\limits_{k \in C_n} e^{V_{nik}}} \tag{2}$$

The selected explanatory variables are purchase price (in logarithmic form) and flight schedule preferences x_j. Flight specific attributes such as morning flight (*MORNING*), flight on Friday (*FRIDAY*), flights in peak months including July and August (*HOTSEASON*) according to flight schedule database are treated as *alternative specific variables* to capture the time of day, days of week and month of year preferences of air passengers. The setting allows us to observe the marginal effect of flight preference changes across advance purchase periods. Furthermore, to identify passengers who often travel around consecutive holidays (more than three days) and special vacation such as Chinese New Year and spring vacation, are also marked as vacation (*VACATION*) tourists. Passengers are assumed to travel at particular periods represent their travel preferences. All the alternative specific variables are expected to decrease as departure day approaches. The descriptive statistics of explanatory variables are reported as Table 6.

4. Results

Table 7 presents the estimation results of the three MNL models by using LIMDEP NLogit software. Results demonstrate that all abovementioned variables are significantly tested with the expected sign. For model comparisons, several performance indices, including log-likelihood statistic at optimal, adjusted rho-square (Koppelman and Bhat, 2006) and Akaikes Information Criterion (AIC) are selected. The optimal log-likelihood values of three models are −2524.61, −4485.71 and −3738.01, respectively; whereas the adjusted rho-square are 0.455, 0.034 and 0.195. In term of two indices, the model based on the equal time period performs best. Additionally, the equal time period model also has the smallest AIC/N value of 2.010, suggesting the proposed temporal segmentation based on equally of 12 days can better explain the advance purchase behaviors.

For the generic variables, the log(PRICE) coefficients in the equal time period model has significantly negative marginal effect of −1.042 on advance purchase as expected, suggesting the higher purchase price, the lower utility of passengers and thus the probability of the airline being chosen decreases. The interaction term between log(PRICE) and morning flights has a negative coefficient of −2.358 which makes that the total of log(PRICE) marginal effect becomes −3.4. The result indicates that purchase price has larger negative effect for the morning flight. In contrast, the interaction terms of HOTSEASON and VACATION flights have a positive effect of 2.713 and 4.853, implies that the passengers' disutility of price effect is lower when passengers travel during hot season or vacation, which results in the price effect turns to be positive. One possible explanation for this could be that we used the transaction records that provides only purchased alternative for modeling. Only the passengers who accepted the higher purchasing price were being recorded in our dataset, passengers who chose to purchase later nor not purchase were unable to capture.

For the alternative specific dummy variables included in the model are aimed to capture the flight schedule preferences across advance purchase periods. All alternative specific variables have the significantly positive effects on utility when compared with base alternative (advance purchase period 1: within 12 days prior to departure). Both MORNING and FRIDAY variables show the expected decreasing pattern. The utility decreases as the advance purchase period approaches departure day, implying that passengers who prefer morning and Friday flights tend to purchase ticket earlier. However, the coefficients of VACATION variables present the positive but irregular effect. One possible reason for this might be that airlines are believed to hold the seats of lower fare class and release them as late as possible before vacation times.

Table 8 further summarizes aggregate direct price elasticities. The elasticities of ordinal flights are determined according to the estimated parameter of log(PRICE) excluding interaction effects. As expected, the longer the advance purchase days are, the higher the direct elasticity. The values of most elasticities are larger than one, indicating that the passengers are sensitive to price changes. The elasticity decreases closer to the date of departure, implying that passengers becomes less sensitive to price as closer to the date of departure. This phenomenon also reflects that once passengers have decided the purchase flight. They may have to make the purchase as departure day approaches, no matter how price changes.

Note: Ordinal flights are defined as the flights are not in the morning, hot season and vacation.

For ordinal flights, Period 5 has the highest elasticity of −1.297, suggesting 1% of log price increases will result in 1.297% decrease of choice probability in Period 5 (>49 days prior to departure), whereas Period 1 (0–12 days prior to departure) has the lowest direct elasticity of −0.371 which is less than one, suggesting the price inelasticity of Period 1 passengers. The elasticities of morning flights are 3 times higher than those of ordinal flights, indicating that passengers preferring morning flights are more price sensitive. Interestingly, popular flights in hot season and vacation, have positive elasticities, suggesting price increases will also result in increase of choice probability. This is mainly because the positive estimated total log price effects of 1.671 and 3.811. The result suggests that passengers may need to spend more for purchasing hot season and vacation flights. However, in this study, our data only reflects the behavior of passengers who accepted the higher purchase price. Passengers may choose alternative flights from other carriers or choose not to purchase. In sum, the elasticity

Table 6
Descriptive statistics of explanatory variables.

Variables	Description	Mean/%	Sd	Med.	Max	Min.
PRICE	Purchase price in thousands New Taiwan Dollars	3.546	0.346	3.450	4.750	3.050
ADVDAYS	Advance purchase days before departure	10.548	11.374	7	60	0
MORNING	Dummy, 1 if morning flight; 0 if others.	31.46%				
FRIDAY	Dummy, 1 if Friday; 0 if others.	21.52%				
HOTSEASON	Dummy, 1 if July and August; 0 if others.	16.97%				
VACATION	Dummy, 1 if consecutive holidays; 0 if others.	11.69%				

Table 7
Estimated results of three models.

Variables/Experiments	Equal time period			Equal number			Professional judgement		
	Coeff.	t-value		Coeff.	t-value		Coeff.	t-value	
ASC2	−1.855	−24.230	***	−0.137	−2.280	**	2.023	21.470	***
ASC3	−2.769	−24.360	***	−0.857	−9.910	***	0.918	8.520	***
ASC4	−3.559	−23.320	***	−0.729	−9.320	***	0.422	3.780	***
ASC5	−4.301	−21.350	***	−0.938	−10.910	***	−0.295	−2.220	**
log(PRICE)	−1.042	−2.160	**				−1.025	−2.660	***
log(PRICE)*MORNING	−2.358	−3.210	***	−2.436	−4.480	***	−1.860	−2.980	***
log(PRICE)*FRIDAY									
log(PRICE)*HOTSEASON	2.713	3.160	***	2.306	3.940	***	2.740	3.930	***
log(PRICE)*VACATION	4.853	5.680	***	2.670	4.140	***	3.890	5.360	***
MORNING (P2)	0.498	4.700	***				0.928	3.840	***
MORNING (P3)	0.526	3.410	***	0.330	2.680	***	1.354	5.440	***
MORNING (P4)	0.691	3.360	***	0.557	5.170	***	1.429	5.660	***
MORNING (P5)				0.615	5.520	***	1.551	5.680	***
FRIDAY (P2)	0.528	4.570	***						
FRIDAY (P3)	0.558	3.360	***	0.413	3.050	***	0.228	1.970	**
FRIDAY (P4)				0.360	2.910	***	0.666	5.680	***
FRIDAY (P5)				0.503	4.040	***			
HOTSEASON (P2)	0.784	6.650	***	0.561	3.410	***	0.443	2.100	**
HOTSEASON (P3)				0.793	4.440	***	1.076	4.930	***
HOTSEASON (P4)				1.149	7.220	***	1.196	5.360	***
HOTSEASON (P5)				0.852	4.850	***			
VACATION (P2)				−0.295	−1.760	*	−0.811	−5.490	***
VACATION (P3)	0.924	5.050	***	−0.499	−2.260	**	−0.690	−3.770	***
VACATION (P4)	1.599	7.370	***						
VACATION (P5)	1.048	2.540	**	0.897	6.260	***	0.671	3.560	***
Goodness of fit measures									
No. of observation		2899			2899			2899	
No. of parameters		17			20			20	
Log-likelihood at zero		−4665.76			−4665.76			−4665.76	
Log-likelihood at constant		−2634.70			−4603.24			−3881.59	
Log-likelihood at optimal		−2524.61			−4485.71			−3738.01	
ρ^2		0.459			0.039			0.199	
Adj-ρ^2		0.455			0.034			0.195	
AIC/N		2.010			3.563			2.972	

Note: ***, **, and * represent reaching 1%, 5% and 10% significance level, respectively.

Table 8
Direct price elasticities.

Advance purchase periods	Ordinal flights	Morning flights	Hot season flights	Vacation flights
Period 1	−0.371	−1.209	0.594	1.355
Period 2	−1.040	−3.391	1.666	3.801
Period 3	−1.196	−3.899	1.915	4.370
Period 4	−1.231	−4.014	1.972	4.499
Period 5	−1.297	−4.231	2.078	4.742

values of morning and vacation flights are larger than other flights, suggesting those two types of flights are more sensitive to price changes, leaving a large room for RM strategies.

5. Conclusions

This study attempts to empirically investigate the advance purchase behaviors of air tickets by using multinomial logit models based on the airline direct transaction data of Taipei-Macau (TPEMFM) route in 2011. To facilitate model development, the advance purchase horizon is divided into five time periods according to three segmentation methods, including equal time periods, time periods with equal number of purchases and time periods according to professional judgment. Explanatory variables including price, flight schedule (time of day, day of week, and months of year) and fare class preferences are examined. In terms of adjusted rho square, AIC value and log-likelihood statistics, the equal time segmentation performs best.

Based on the estimated coefficients, the log price has negative effect of −1.042 on advance purchase, suggesting the higher price, the lower utility of passengers. The interaction terms for HOTSEASON and VACATION have positive effects, implying that the passengers' disutility of price is lower when passengers travel during vacation time. As for dummy variables, the MORNING and FRIDAY show the expected decreasing pattern as departure day approaches, indicating that passengers prefer morning and Friday flights generally purchase ticket earlier in advance. The irregular pattern of VACATION variable reflects the behavior of the airline RM strategies by holding and releasing seats for vacation flights. Additionally, based on the direct and cross-elasticity analysis, the extent of advance purchase behavior with respect to price strategy is also revealed.

The online ticket transactions data investigated in this study only account for low percentage of whole advance purchase records. However, with the rapid popularity of the online purchase channel promoted by airlines, the proposed model can be further examined by the dataset which is able to better represent larger percentage of advance purchase behaviors. The average price present here could be further incorporated the dynamic pricing models to better reflect airline competition (Bilotkach et al., 2010) and the price change in the advance purchase time variation (Escobari, 2012; Deneckere and Peck, 2012). Unfortunately, our dataset does not allow us analyzing choices among alternative flights and carriers nor "not fly" alternative. To date, Escobari and Mellado (2014) have been empirically studied advance purchase behaviors of air tickets in a dynamic setting with revealed preference data where the information of all options is available.

Additionally, the study route is a short-haul air route (Taipei-Macau). It is believed that the advance purchase behaviors of long-haul air routes should be remarkably different. The comparisons deserve a further study. Since the dataset does not contain the socio-economic variables and trip characteristics of air passengers, similar models with considering more valuable explanatory variables should be estimated based on a questionnaire survey on air passengers so as to draw more policy implications for RM strategies. Compared with discretely divided the temporal segmentation of advance purchase horizon, future studies can consider to consider the temporal correlation among periods or to adopt continuous Logit models to further enhance model performance.

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