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Advance purchase behaviors of air tickets

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ABSTRACT

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