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Homogeneous service with heterogeneous products: Relationships among airline ticket fares and purchase fences☆

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ABSTRACT

A fare table derived from homogeneous service is essential for revenue management applications in the airline industry. Restrictions or so-called fences are usually regarded as a useful tool to differentiate homogeneous seat service. Nevertheless, the relationships among fares and fences are not yet clear. This study aims to investigate passengers' preferences on the choice of ticket alternatives describing by fares and fences and using Taiwan domestic air travel as an example. Regarding the attributes that an airline ticket may be attached such as departure time, booking time, ticket validity, changing fee, refund and fare, stated preference questionnaires are developed with multiple hypothetical scenarios for respondents to select in the experiment. 398 valid samples are collected for the logit model analysis. With the use of mixed logit model to accommodate both passengers' heterogeneity and also the issue of relevant alternatives in the experiment, the results show statistical significance of all applied attributes with correct signs. In addition, passengers possess different attitudes on the fence of booking time, ticket validity, changing fee, and fare. Willingness-to-pay of each fence is further calculated to ultimately generate a fare table based on the combination of fences for practice use.

1. Introduction

The concept of revenue management (RM) is widely adopted by airline operators to take advantage of market segmentation and create seat-based differential services to attract passengers from different segments. The use of RM is not new but getting more and more important since market competition is getting fierce especially after the entry of low-cost airlines (Fageda et al., 2011). Regarding the contribution of RM to different industries in reality, Rannou and Melli (2003) find 3%–7% revenue increase in an airline simulation study. In addition, Kimes (2005) also show that the utilization of RM may bring 3%–5% extra revenues in the airline, hotel, and rental car industries. With obvious potential for revenue increase, the application of RM has become popular and widespread in many other fields (Chiang et al., 2007; Anderson and Xie, 2010; Cross et al., 2011; Haddad, 2015).

RM constitutes of four vital pillars namely forecasting, pricing, overbooking, and seat allocation. The role of pricing provides essential fare information to form booking classes and avoid the commoditization of service in order to optimize the use of perishable seat resources (Bobb and Veral, 2008; Anderson and Xie, 2010). With the structure of booking classes or, in other words, the fare table, the tasks of forecasting, overbooking, and seat allocation can then be implemented consequently in the quantity-based RM system (Talluri and van Ryzin, 2004). Taking economic seats for instance, airline operators may simultaneously manipulate multiple booking classes with respective codes such as Y, M, L, and V for a specific origin-destination during the reservation period (Obermeyer et al., 2013; Alderighi et al., 2012). Although these classes all belong to the economic cabin, they may have very different fares due to using conditions. However, the relationships among fares and fences are seldom addressed. In a recent review, Guillet and Mohammed (2015) indicate that price framing, price value relationship, and price competition receive limited attention within the topic of RM pricing.

The determination of booking classes toward homogeneous seat service can be observed and discussed from two perspectives. From the supply side, airlines may consider various factors including operating costs to generate fares for different cabins. The Civil Aeronautics Board in the United States establishes a "Standard

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Industry Fare Level (SIFL)" and periodically updates the SIFL by the percentage change in airline operating cost per available seat-mile. The established SIFL can then be regarded as a reference to form the unrestricted coach fare (USDOT, 2015). International Air Transport Association (IATA) also publishes Passenger Air Tariff (PAT) which contains three types of fares namely unrestricted normal fares, restricted normal fares, and special fares (PAT, 2015; Chang, 2006). Among them, special fares as known as promotional fares are usually applied to stimulate demand during off-peak periods.

On the other side of the coin, understanding how passengers make their ticket choices while facing multiple alternatives is also informative and vital. For instance, some passengers may choose to purchase tickets on-line at low prices with a requirement to pay in advance and also penalties for changing itineraries. Other passengers with less price sensitivity may choose to pay high prices for tickets with more flexibility. Generally speaking, different segments of passengers may have distinct valuations toward homogeneous seat service and result in an opportunity for airlines to deploy market segmentation and differential pricing (Zhang and Bell, 2012). In addition, with intense dynamics and competitions in the airline market, Ratliff and Vinod (2005) argue that more advanced pricing and RM decision support tools are required in the conventional use of fare availability as the primary means of segmentation.

In the literature, related works focus on the choice of airline carriers or flight service by considering different combinations of service-centric attributes such as in-flight service or seat comfort with corresponding air fares (Balcombe et al., 2009; Wen et al., 2009). Some other papers address the issue on how to determine the number of seats that each booking class should sell given different assumptions (Kim, 2015). Alderighi et al. (2012) address the competition in the European aviation market through mapping relationships among airfares and economic variables. Nevertheless, relatively limited works in the literature focus on how passengers make their choices of tickets (or booking classes) in terms of RM-centric attributes. In practice, RM-centric attributes are usually utilized to differentiate homogeneous seat service by adding restrictions or so-called fences, which are rules that a company uses to determine who gets what price (Kimes and Wirtz, 2003), onto the ticket. As Anderson and Xie (2010) argue in their paper, an important task in RM is to set prices to avoid commoditization of the service and the use of fences may be an effective way to exclude certain segments from specific low fares. As a result, this study aims to contribute to the literature by exploring passengers' preferences on booking classes via the use of RM-centric attributes given homogeneous airline seat service (ie. the same OD/airlines/cabin/seat comfort/in-flight service). With such demand driven preferences of fare classes on hand, airline operators may be able to design a fare table that not only satisfies passengers' needs but also ultimately attracts their attention in the competitive airline market.

2. Literature review

2.1. Service-based attributes

While considering choice preferences in the airline context such as choices of airport, airline carriers and flight service, service-based attributes are commonly investigated as summarized in Table 1. First of all, variables related to airlines such as flight frequency, frequent flyer program, aircraft type, punctuality, check-in service, ground service, airline brand, fairness, access time, online reviews, baggage fees, and safety information are commonly regarded as important variables (Garrow et al., 2007; Hess et al., 2007; Teichert et al., 2008; Wen et al., 2009; Wen and Lai, 2010; Mathies et al., 2013; Gao and Koo, 2014; Yang et al., 2014; Jung and Yoo, 2014; Koo et al., 2015; Scotti and Dresner, 2015). Other works focus on the features of flights themselves when passengers face several choice alternatives such as schedule time, the number of stopovers, seat comfort, in-flight service, and in-flight travel time (Ortúzar and Simonetti, 2008; Balcombe et al., 2009; Wen et al., 2009; Wen and Lai, 2010; Mathies et al., 2013; Gao and Koo, 2014; Koo et al., 2015). However, all these papers address the choice of non-homogeneous service which may be somehow differentiated by different brands, different markets, different seat service, or different airports. Regarding the application in RM, usually operators need to think about the allocation of homogeneous seat service, which is the research target in this study, for achieving high revenues.

Differentiating homogeneous seat service by adding fences onto the ticket is essential for airline operators to structure booking classes. Although fences are commonly seen while purchasing airline tickets in practice such as departure time, booking time, and premium charges, the real effects of fences are not fully explored yet. In the context of flight service selection, Mathies et al. (2013) have addressed the influence of cancellation fees and time of ticketing. Another work by Denizci Guillet and Xu (2013) also investigate the influence of advanced purchase, refundability, and changing fees on the selection of different flight service. Nevertheless, none of the research investigates the effect of fences on the selection of homogeneous seat service. In this study, the attention will be focusing on the empirical test of fences when passengers face several alternatives. Through understanding the influences of fences from demand perspective, operators may be able to design a more customer-oriented fare table.

2.2. Restrictions and fences

Although individual passengers may regard one specific service with distinct values and are willing to pay different prices in order to use the service, maintaining perceived fare fairness is critical and also essential while practicing differential pricing (Kimes, 2002). The objective here is to ensure that customers are satisfied with the provided service and do not feel ripped off (Haddad, 2015). This is because if passengers perceive differential pricing with attached fences as fair, they are more willing to accept the practice and increase the purchase intention (Chung and Petrick, 2012). In a recent study, Lin and Huang (2015) also suggest that hotel operators should facilitate the RM knowledge and the fairness perception of their customers so as to both effectively utilize resources and provide diversified services. The fairness of fences should depend on whether passengers perceive them to be acceptable or not. In the literature, studies show that familiarity with RM applications are helpful for consumers to perceive RM applications to be fair (Choi and Mattila, 2005; Wirtz and Kimes, 2007; Lin and Huang, 2015).

The reason for building fences is to avoid the phenomenon of spillover which is the migration of passengers from high-paid segments to low ones. Several types of fences have been introduced and applied widely in the service industry. Wirtz and Kimes (2007) have categorized lodging fences into physical and non-physical types. Physical fences contain product characteristics (room class, car size, seat location), amenities (free meal, free cart, valet parking), and service level (priority wait-listing, exclusive check-in counter, personal butler). On the other hand, non-physical fences include time of booking, booking channel, ticket flexibility, time of use, location of consumption, membership, and size of group. In addition to the above non-physical fences, Chen et al. (2011) explore the influence of cancellation in an experiment and show the impact of cancellation deadline on booking decisions. Zhang and Bell (2012) review related works and categorize fences

Table 1
Related airline preference studies.

Authors	Years	Target	Attributes
Garrow et al.	2007	Flight	Departure time, arrival time, total time in air, total trip time, legroom space, and airline carriers, price
Hess et al.	2007	Airport and airline	Frequent flyer information, connections, aircraft type, on-time performance, airport/airline inertia variables, price
Teichert et al.	2008	Airline	Flight schedule, total fare flexibility, frequent flyer program, punctuality, catering, and ground service, price
Ortúzar and Simonetti	2008	Mode	Travel time, comfort, and service delay, price
Balcombe et al.	2009	Flight	Seat pitch, seat width, in-flight meal, in-flight entertainment, and complementary in-flight drinks, price
Wen et al.	2009	Airline	Preferred departure time, flight frequency, punctuality, check-in service, seat space, food quality, cabin service, price
Wen and Lai	2010	Carrier	Schedule time difference, flight frequency, on-time performance, check-in service, seat space, food and beverage service, cabin crew service, price
Collins et al.	2012	Flight	Cost, departure time, arrival time, duration, stopover, plan type, seat pitch, availability of seat allocation, entertainment, itinerary change cost
Mathies et al.	2013	Flight	Routing, travel time, cancellation fee, ticketing, frequent flyer program, award flight, validity of frequent flyer points, upgrade, fairness adjustment, price
Denizci Guillet and Xu	2013	Flight	Advanced purchase, refundability, changing fees, price
Gao and Koo	2014	Carrier	Inflight service, airfare, safety, entry visa requirement, transit experience, price
Yang et al.	2014	Airport and route	Airport frequency, aircraft seats, punctuality, and check-in time, fare, flight time, number of airlines, route frequency, departure time, price
Jung and Yoo	2014	Airline	Access time, journey time, price
Koo et al.	2015	Flight	Schedule, in-flight service, travel time, safety information, price

into three types namely purchase pattern, product characteristics, and customer characteristics. Among them, constraints such as booking time, purchase time, and channels are related to purchase pattern. Product-based fences are like product usage, alternation charge, transaction cost, service option, and information vagueness. Customer characteristics are commonly known as demographic variables such as age, group, budget, and loyalty. In this study, those fences which can be attached on the homogeneous seat service will be considered.

On empirical findings of fences, Mathies et al. (2013) adopt multinomial logit model (MNL) to investigate the influence of customer-centric attributes on the choice of airline services. They find that cancellation fees may have significant effects on passengers' flight choices in all segments except business travelers. In addition, for the attribute of time of ticketing, Mathies et al. (2013) indicate that only booking 60 days before departure causes negative impacts on utility in the segments of loyal leisure and business travelers. In another study, Denizci Guillet and Xu (2013) explore the effect of advance requirement, refundability, and changeability on choosing flight services. Based on the relative importance score from the result of conjoint analysis, advance purchase is regarded to be the most important fence followed by refundability and changeability (Denizci Guillet and Xu, 2013). Nevertheless, no further statistical tests and willingness-to-pay information are reported in their study.

2.3. Fare discounts

Fences are almost always accompanied by discounts. Full fare is initially determined. Corresponding fences and discounts are then attached to yield various booking classes with different levels of ticket flexibility. Usually, strict restrictions come with heavy discounts, and vice versa. For instance, Law and Wong (2010) investigate ninety seven hotel room rates with terms and conditions and find that more favorable terms and conditions result in higher prices. Chen et al. (2011) indicate that the closer the cancellation is to the day of consumption, the harder it is for the consumers to receive full refund for their reserved service. Other related works, such as Yoon et al. (2010) and Nusair et al. (2010), show the importance of price framing which price formats and price discounts both have significant impacts on customers' perceptions. In short, it is critical for airline operators to know the trade-off relationships between prices, discounts, and fences.

In order to determine the monetary value of fences, the calculation of willingness-to-pay (WTP) becomes informative and essential. In the literature, several fashions are available for computing WTP values such as regression (Reynisdottir et al., 2008) and contingent valuation method (Shono et al., 2014). Discrete choice models are intrinsically capable of calculating monetary values of attributes. Hensher et al. (2005) obtain WTP values by calculating the ratio of an attribute estimate and the price coefficient, where both coefficients are statistically significant. This procedure is then commonly applied in the literature. For example, Wen et al. (2009) utilize the result of parameter estimation to obtain WTP values of the service-based attributes and conclude that passengers are willing to pay more for quality service in the long-distance flight journey. Balcombe et al. (2009) also apply discrete choice models to compute consumers' WTP for in-flight service and comfort levels. In short, they find that in principle passengers are willing to pay a relatively large amount for enhanced service quality. Another similar study is by Garrow et al. (2007) who apply logit family models to figure out WTP values of air service improvement. With the support from these applications and findings, the calibrating results of discrete choice models may be a straightforward method to compute WTP of RM-centric attributes. More importantly, through investigating the WTP values of fences, this study may be able to provide a fare table which shows the trade-off effect among fences and fares and bridges the research gap in the literature.

2.4. Passenger heterogeneity

Passengers, in fact, may have non-homogeneous behaviors towards the same flight service (Wen et al., 2009; Balcombe et al., 2009; Zhang, 2012). The source of heterogeneity may be caused by different socio-economic characteristics such as gender, income, and age (Heo and Lee, 2011; Grigolon et al., 2014). Even for the same service or product, two individuals who share very similar socio-economic status may make different decisions due to their experiences such as knowledge, taste, consumption frequency, and involvement (Martinez et al., 2006). In a recent study, Yang and Lau (2015) also confirm that different generations (X vs. Y) may possess different attitudes toward the loyalty in the hotel industry. For instance, Generation X is value-centered in building loyalty;

Generation Y focuses both on value and upscale quality features. Instead of using socio-economic, experiences, generations as variables to distinguish differences among groups, some other works utilize the cluster analysis to divide the whole market into several segments and tackle the issue of heterogeneity such as Adhikari et al. (2013) on the pricing of the upscale dining experience and Tsai and Chen, 2016 on the choice of souvenirs.

In the family of discrete choice models which are derived from random utility theory, mixed logit model (ML) is the prototype to incorporate the consideration of non-homogeneous behaviors and have the ability to approximate any choice model given appropriate mixing distributions (Koo et al., 2015). In addition, MNL also assumes that all alternatives are independence of irrelevant alternatives (IIA) and may not be appropriate for alternatives with dependence. Due to the form of ML which has a mixture of logits, the probabilities of ML do not exhibit IIA (Brownstone et al., 2000; Hensher, and Greene, 2003). As a consequence, the advanced and flexible mixed logit model is applied to tackle the phenomenon of passenger heterogeneity and also relax the assumption of IIA in the empirical study.

Wen et al. (2009) compare the performance of MNL and ML to investigate how passengers choose international airlines from Taiwan to Japan. Based on the modelling results, they have shown that ML models which include random parameters of service attributes may adequately capture the random heterogeneity in air travelers' preferences. Balcombe et al. (2009) also applies ML model to compute passengers' WTP values for in-flight service and comfort levels. They found that the constructed model may indicate valuable attributes and provide useful WTP information for the purpose of product differentiation. Based on what have been reviewed in the literature, this study also utilizes ML as a vehicle to fit passengers' preferences and compares its outcome with conventional MNL models in the empirical study.

3. Methodology

3.1. Alternatives, attributes, and levels of service

Stated preference experiments are able to obtain behavioral responses of individuals (Collins et al., 2012) and have become a popular way for data collection in the field of consumer research. In the experiment, several hypothetical scenarios describing by attributes and corresponding levels of service are rendered. Each hypothetical scenario may have multiple alternatives for respondents to choose. In this study, a domestic air market in Taiwan is studied and regarded as a case for illustrating the procedure to structure booking classes. Three ticket alternatives are adopted and they can be distinguished by channels namely airline website, online travel agency, and kiosks in the convenience store. The reason why the attribute of selling channel is included in the experiment is because it provides a source of difference among alternatives with the same combinations of the attributes in the experiment (Table 3) under the use of the orthogonal table. In addition, these three channels are selected due to their popularity for the domestic air market in Taiwan. In the choice model, the effect of the selling channel would be captured by alternative-specific constants; the influences of the adopted fences are presented by the estimation of generic variables.

Based on what have been reviewed in the literature about RM-centric attributes, five fences plus ticket fare of a weekend trip (ie. Friday to Sunday) are utilized in this study to investigate the relationships among fares and fences for an economic seat with the same route, same company, same cabin, same seat comfort, and also same in-flight service. The reason why a weekend trip is targeted is because it has significant fluctuation of demand in the research target. The five applied attributes are departure time, advance purchase, ticket validity, changing fee, and refund as shown in Table 2 and described below.

First of all, departure time as a fence is prevailing in practice for balancing demand and supply. Usually when passengers choose to depart during peak periods with prosperous demand, they should expect to pay more than those flights which leave during off-peak hours. On the other hand, passengers would get a discount as a reward if they choose to depart during off-peak periods. In terms of the real situation in the target market, flights departing in the Friday morning are regarded to be off-peak choices. The peak hours are from Friday noon to Saturday noon. For the rest of the weekend, the period is regarded to be general. Regarding the expected sign of the attribute, passengers should be prone to depart during peak hours to have preferred arrival time. As a result, if off-peak flights are taken as the base, those departing during general and peak hours would increase passengers' utility and should result in positive estimates (Table 2).

The second attribute is booking time or advance purchase which is the time point where passengers have to make their reservations and pay up before taking off. For the research market, usually reservations start two months before departure. In this study, we divide the whole booking period into three sequences which are booking 31–60 days before departure, 15–30 days before departure, and within two weeks before departure, respectively. Since early booking (or early bird) reduces the uncertainty for the airlines, tickets with advance purchase usually obtain a discount as a reward. However, early booking would decrease passengers' utility since they lose some sort of flexibility while planning itineraries. As a consequence, if booking 31–60 days before departure is regarded as the base, tickets with shorter periods for advance purchase would increase passengers' utility and should result in positive estimates.

The third attribute is ticket validity which restricts the period that tickets can be used. The current practice for the research market is twelve-month validity which is also a common practice adopted by the international airlines. In order to investigate the effect of other length of validity to enrich the structure of booking classes, three periods of validity are considered in this study. Except the original twelve-month validity, other two levels of service namely six-month and one-month are also considered, respectively. Since shorter validity forces passengers to use the tickets as quickly as possible, it usually accompanies with a larger discount. Nevertheless, short validity makes the ticket less flexible to use in comparison with a ticket with long validity. As a result, if twelve-month validity is taken as the base, tickets with shorter validity would decrease passengers' utility and should result in negative estimates.

For passengers who have already paid up the price after the reservation and need to alter their original itineraries, a premium charge (ie. changing fee) would be incurred. The current practice in the studied case is free of charge which is quite nice and generous for passengers who have the need for itinerary change. Another two possibilities are considered in this study and they are 10% service charge of ticket price and no change allowed at all. Since no change allowed and 10% service charge both force passengers to stick to their original plans, the fences usually accompanies with discounts. In the direction of making passengers strictly stick to their original plans and prevent them from transferring to other substitute service, another useful fence is refund. Refund can be seen as a sort of switching cost while making cancellation decisions. The current practice in the research market is to have 90% refund if passengers decide to cancel their trips. Another possible level which is no refund at all is included in the experiment to test its effect. Both the fences of changing fee and refund make

Table 2
Attributes, levels, and corresponding discounts.

Attribute	Level	Coding	Exp. Sign	Discount factor
Departure time	Off-peak	0.0	Base	0.80
	General	1.0	+	0.90
	Peak	0.1	+	1.00
Booking time	31-60 days before departure	0.0	Base	0.80
	15-30 days before departure	0.1	+	0.90
	Within 14 days before departure	1.0	+	1.00
Validity	12 months	0.0	Base	1.00
	1 month	1.0	−	0.80
	6 months	0.1	−	0.90
Changing fee	No change allowed	0.0	Base	0.90
	10% ticket fare	0.1	+	0.95
	Free of charge	1.0	+	1.00
Refund	No refund	0	Base	0.95
	90% refund	1	+	1.00
Fare	Vary with fences	Real	−	na

passengers scarify some sort of flexibility while using tickets, the use of them should decrease passengers' utility. More specifically, for the fence of changing fee, if no change allowed is regarded as the base, tickets with flexibility to alter itineraries would increase passengers' utility and should result in positive estimates. Similarly, for the fence of refund, if no refund is regarded as the base, then 90% refund would increase passengers' utility and should result in positive estimates.

Last but not least, the combination of the applied attributes with different levels of service may result in the spectrum of ticket price. It should be noted that it is not possible for us to obtain precise discount information for each fence since this kind of information is simply just unavailable or regarded to be confidential by airlines in reality. In addition, calculating the monetary values of different fences is one of the objectives that this study aims to attain. As a consequence, in order to have reasonable discount assumption, this study gathers qualitative feedback from the industry through interviews. First of all, we set up the fundamental rule among fences and fares which stricter fences should result in larger discounts. Then we have a presumed version of Table 2 based on the status quo and obtain feedback from airline managers. With trivial modifications, Table 2 is utilized to calculate the ticket fare. Table 3 shows the experimental design of this study which implies a huge amount of cases if a full factorial experiment is conducted ($2^3 \times 3^{12}$ cases). Since such a huge number of test is not possible, the orthogonal table ($L_{36}(2^3 \times 3^{12})$ is then applied in this study to conduct a fractional factorial experiment with 36 scenarios. Then these 36 scenarios are randomly assigned to form six subsets, each of which consists of six different scenarios. As such, each respondent needs to evaluate only one randomly assigned subset. Table 4 shows an example of scenarios in the questionnaire. Similar implementations of the orthogonal table and also the choice experiment can be retrieved in the literature (Wen et al., 2009; Chen and Chen, 2012).

3.2. Discrete choice models

Discrete choice models are derived from random utility theory for the objective of utility maximization. Each discrete choice model may measure the utility of alternatives via utility function containing systematic and random error components as shown in Equation (1) where V_{it} is the systematic component and ε_{it} is the error term for passenger t to select alternative i. In addition, X_{it} is a vector of attributes and β is a vector of parameters associated with X_{it}.

Among the family of discrete choice models, MNL is the most popular and widely applied prototype which assumes the error of the utilities to be independent and identically Gumbel distributed. Given such a condition, the probability for passenger t to select i from j alternatives can then be specified as Equation (2). Nevertheless, MNL has the assumption of independence from irrelevant alternatives (IIA) which may cause estimate bias if alternatives are not fully irrelevant.

$$\mathrm{U_{it}} = \mathrm{V_{it}} + \varepsilon_{\mathrm{it}} = \beta' \mathrm{X_{it}} + \varepsilon_{\mathrm{it}} \tag{1}$$

$$\mathrm{P_{it}} = \mathrm{prob}\left[(\mathrm{U_{it}} > \mathrm{U_{jt}})\right] = \frac{e^{V_{it}}}{\sum_j e^{V_{jt}}} \tag{2}$$

ML is a generalized extension of MNL with not only the consideration of individual heterogeneity but also the capability of releasing the assumption of IIA in MNL (Train, 2009). Essentially, each alternative in the model still has a corresponding utility function. Instead of assuming parameters to be constant over individuals, ML allows them to vary over passengers with a density function $f(\beta|\theta)$. The ease of the restriction of constant parameter makes ML more flexible than MNL and can deal with random heterogeneity of preferences among passengers. In most

Table 3
Experimental design of the study.

Alternative	Departure time	Booking time	Validity	Changing fee	Refund	Fare
Airline website	Off-peak	31–60 days before departure	1 month	No change allowed	No refund	
	General	15–30 before departure	6 months	10% ticket fare	90% refund	
	Peak	Within 14 days before departure	12 months	Free of charge		
Online travel agency	Off-peak	31–60 days before departure	1 month	No change allowed	No refund	
	General	15–30 before departure	6 months	10% ticket fare	90% refund	Base on the combination of fences
	Peak	Within 14 days before departure	12 months	Free of charge		
Kiosk	Off-peak	31–60 days before departure	1 month	No change allowed	No refund	
	General	15–30 before departure	6 months	10% ticket fare	90% refund	
	Peak	Within 14 days before departure	12 months	Free of charge		

Table 4
Example of a scenario in the questionnaire.

Tick one	Alternative	Departure time	Booking time	Validity	Changing fee	Refund	Fare
A.	Airline website	Peak	Within 14 days before departure	6 months	Free of charge	No refund	$2257
B.	Online travel agency	Off-peak	31–60 days before departure	12 months	10% ticket fare	No refund	$1449
C.	Kiosk	Peak	Within 14 days before departure	1 month	No change allowed	No refund	$1752

applications, ML adopts continuous distribution function for $f(\beta|\theta)$ such as normal, lognormal, uniform, and triangular functions where θ in the density function characterizes mean and variance. The utility function of ML may be described as Equation (3) where β_t are random parameters, X_{it} is a vector of collected variables, and ε_{it} has independent and identical distribution of error terms. Still the error terms are assumed to follow an independent and identical Gumbel distribution, the unconditional probability of choosing alternative i is then the integral of the conditional probability with MNL form over β of the density function $f(\beta|\theta)$ as shown in Equation (4). The ML probability does not have a closed form and parameters can be approximated by using simulation techniques. All parameters in ML are obtained by using NLOGIT software in this study.

$$U_{it} = \beta_t' X_{it} + \varepsilon_{it} \tag{3}$$

$$P_{it} = \int \left(\frac{\exp(\beta' X_{it})}{\sum_{j=1}^{J} \exp^{\beta' X_{jt}}} \right) f(\beta|\theta) \mathrm{d}\beta \tag{4}$$

3.3. Data collection

Kinmen, also known as Quemoy in some western countries, is a small island located off the southeastern coast of China (Fig. 1). As a traditional island, Kinmen is full of war history, heritage of cultures and natural resources. Especially Kinmen is famous for those military forts, tunnels, and constructions built during the Cold War Era. Since 1949, battles or conflicts have occasionally occurred between the People's Liberation Army in China and the Nationalist Army in Taiwan. Meanwhile, the order of martial laws was implemented on the Island, and not until 1993 was the ban on tourists from Taiwan to Kinmen lifted. Since then, Kinmen has developed tourism as its approach of economic development. In the beginning of the 21st century, owing to a rapprochement between the governments of People's Republic China (China) and Republic of China (Taiwan), the suspension between Kinmen and China over the past nearly 50 years was ended by a so-called "Mini Three Links (mail, transportation, and business)" policy that leads to the growing transparency and legitimization of tourist movements. As a result, Kinmen was formally opened to Chinese tourists in 2005. It is now a popular tourist destination for Taiwanese and Chinese alike and is known for its quiet villages, coastal resources, old-style architecture and war remains.

The targeted market in this study is from Taipei to Kinmen (broken line in Fig. 1). The survey population is passengers who are between 18 and 65 years old since those who age over the range may be eligible for teen/senior discounts and beyond the scope of this study. A pretest of the questionnaire only suggested minor changes on wordings. Face-to-face interviews were then conducted with airline passengers at the terminal in Kinmen from October to December 2013. Trained interviewers first explain what the fences are and what possible discounts they may receive if accepting fences. The surveying process was carried out on both weekend and weekday, from 9 a.m. to 6 p.m. The principle of systematic sampling with randomness was adopted. Finally, four hundred and thirty questionnaires were distributed and three hundred and ninety eight valid samples (response rate = 93%) are collected for the following empirical analysis.

4. Empirical results

4.1. Demographic profile of respondents

As indicated in Table 5, the collected samples consist of 60% male passengers. For the dimension of age, the 18–30 year-old group composes 33.42% of the samples and followed by 31–40 year-old (30.65%) and 41–50 (22.86%). For the feature of occupation, the table shows that respondents are from various career categories where business (25.88%) has the largest portion. Among all samples, 75.38% of them possess college degree and above. For the variable of monthly income (in local currency), the result is also multifaceted without concentration of one category over the other. Most of them usually take the domestic flight fewer than three times a year.

When asking about their current trips, 66.3% of the samples were having trips fewer than five days. For the question of price reasonableness about the status quo of the studied market, 69.1% of the samples regard price reduction to be necessary in the future and 10.8% of them show neutral attitude. While asking about different fences with discounts, respondents are prone to early-bird and off-peak discounts. For the changing fee/refund discount, 41.7% of the interviewers agree with the implementation and 22.6% of them possess neutral attitude.

4.2. Empirical results

A MNL model is first estimated using respondents' preferences for ticket alternatives. In the model, the effects of departure time, booking time, validity, changing fee, refund, and fare are analyzed. All the attributes except fare are dummy coded. The estimation results of MNL models are summarized in Table 6. The outcome of MNL model is actually not as good as expected since only the fences of changing fee, refund, and fare show significance at 95% confidence level with correct signs. Other adopted attributes such as departure time, booking time, and validity are not statistically significant in the MNL model. More specifically, tickets with flexibility to change itinerary at no cost, comparing with the low level as the base (no change allowed), will increase passengers' utility ($\widehat{\beta} = 0.724$). Even if 10% of ticket price is charged for itinerary change, it still increases the utility ($\widehat{\beta} = 0.470$) comparing with the strictest fence of no change at all. As a result, respondents prefer to have flexibility of altering their itineraries when necessary which quite echoes the reality.

For the attribute of refund, the result shows that passengers prefer to have 90% of ticket price back comparing with the base level of no refund if they decide to cancel trips. The outcome shows plausibility since refund implies flexibility when using the ticket and stricter fences do result in larger utility reduction. In addition, it is interesting to note that respondents seem to value changing fee more than refund since the estimation of 90% refund ($\widehat{\beta} = 0.223$) is less than that of 10% ticket price for itinerary change ($\widehat{\beta} = 0.470$). In

Fig. 1. Map of Kinmen Island (Data resource: Google map).

fact, passengers usually cancel their trips in two situations in the study case. The first situation is that passengers regard their trip to be no more necessary in the future and cancel trips by their own will. The other situation is that the ticket is beyond the validity so that the ticket is no more valid. In this situation, passengers will be forced to cancel their trips if they want refund; otherwise, the ticket has no value at all one year after the validity. In short, it is more common for domestic passengers in Taiwan to have itinerary changes rather than cancellation which justifies the outcome why the variation of changing fee has a higher influence than that of refund. The attribute of fare, aligned with the prior knowledge in Table 2, has a negative impact on the choice of ticket alternatives. As a result, the trade-off effect among fares and ticket fences do exist and passengers need to pay for having flexibility. The overall Likelihood ratio index ρ^2 of MNL is 0.123.

Regarding the assumptions of MNL, IIA can be regarded as a strong one. Since alternatives in this study (airline website/online travel agency/convenience store kiosk) are not fully irrelevant, the assumption of IIA may not be satisfied and result in the estimate bias such as the insignificance of departure time, booking time, and validity in Table 6. Although these three fences have not been simultaneously researched in the literature, they are widely adopted and practically proved to be useful. As a result, ML, which is a more sophisticated choice model than MNL with the consideration of heterogeneity and also free of IIA (Brownstone et al., 2000; Hensher, and Greene, 2003; Train, 2009) is further utilized to calibrate the survey data.

Modelling results of ML with a density function for parameters ($f(\beta|\theta)$) are summarized in Table 7 and termed ML1. Normal distribution is used in this study for calibrating parameters. In ML1, as expected, the mean of the proposed five fences are all significant at 95% confidence level with correct signs. First of all, departing during peak and general periods may increase utilities comparing with the base of off-peak period since passengers may arrive at their preferred time. Moreover, departing during peak periods (5.494) may obtain higher utility than leaving during general hours (2.472). Secondly, if passengers choose to reserve tickets when the booking date is close to the departure day, then utility will significantly increase comparing with the base of reserving tickets 31–60 days before departure. In fact, passengers prefer not to book too far in advance since booking within 14 days have a higher estimate (5.789) than booking between 15 and 30 days (3.197). Thirdly, long ticket validity may result in utility increase because passengers may use tickets with enough time flexibility. This can be seen from the result that the estimation of one-month validity (−5.759) is actually higher in absolute value than that of six-month validity (−2.645). For the attributes of changing fee, refund, and fare, the results in Table 7 show consistent outcomes with those in Table 6. However, the estimates of changing fee, refund, and fare all have much larger values than those in MNL. In short, passengers prefer to have flexibility of altering itineraries and having refund when they decide to change or even cancel the trips.

The ML1 model also renders heterogeneity information via the calibration of standard deviation of $f(\beta|\theta)$. As shown in Table 7, only standard deviations of departure time, refund, booking time (15–30 days), and changing fee (10% of ticket price) do not have statistical significance. The standard deviations of booking time (within 14 days before departure), ticket validity (both one-month

Table 5
Profiles of respondents.

Variable	%	Variable	%
Gender		**Trip length**	
Male	60.05	<5 days	66.3
Female	39.95	5-14 days	17.1
		14-60 days	11.1
Age		>60 days	5.5
18–30	33.42		
31–40	30.65	**Price reasonableness**	
41–50	22.86	Reasonable	10.8
51–60	10.30	Price rise	2.8
61–65	2.77	Price down	69.1
		Neutral	17.3
Occupation			
Student	13.07	**Early-bird discount**	
Public sector	15.58	Very agree	27.6
Service industry	16.33	Agree	59.5
Industrial	13.81	Neutral	10.6
Business	25.88	Disagree	1.8
Self-employed	15.33	Very disagree	0.5
Education		**Off-peak discount**	
Junior	4.27	Very agree	12.8
Senior	20.35	Agree	66.8
University	75.38	Neutral	14.6
		Disagree	5.3
Monthly income		Very disagree	0.5
<10 k	11.31		
10 k~20 k	6.03	**Change & refund discount**	
20 k~30 k	13.82	Very agree	3.8
30 k~40 k	15.83	Agree	37.9
40 k~50 k	14.07	Neutral	22.6
50 k~60 k	17.08	Disagree	29.1
60 k~70 k	7.54	Very disagree	6.5
>70 k	14.32		
Annual frequency			
1-3 times	49.75		
4-6 times	24.12		
7-9 time	8.54		
>10 times	17.59		

Table 6
Results of multinomial logit model.

	Coefficient	t value
Constants for alternatives		
Kiosk	0.249**	3.326
Online travel agency	0.387**	5.862
Departure time		
General	−0.193	−0.930
Peak	0.155	0.387
Booking time		
15–30 days before departure	0.299	1.443
Within 14 days before departure	0.480	1.206
Validity		
1 month	−0.307	−0.760
6 months	−0.055	−0.264
Changing fee		
10% of ticket price	0.470**	4.337
Free of charge	0.724**	3.865
Refund		
90% Refund	0.223**	2.271
Fare	−0.003**	−2.98
LL(B)	−2300	
LL(const)	−2580	
LL(0)	−2623	
ρ^2	0.123	

and six-month), changing fee (free of charge), and fare all have significant results. The outcome of ML1 not only partially verifies passengers' heterogeneity on the applied fences but also releases the assumption of IIA and shows significant estimates of the fences.

In order to recheck the influence of heterogeneity, we also exclude attributes with insignificant standard deviations and re-estimate the ML model which is termed ML2 in Table 7. The results of ML2 are in fact quiet similar to those of ML1. The overall Likelihood ratio index ρ^2 of ML1 is 0.137. In addition, ML2 is more parsimonious than ML1 since all estimates in ML2 are statistically significant.

4.3. Monetary values of fences

In order to obtain a fare table based on RM-centric attributes, WTP of each fence is then calculated to quantify its monetary value based on the ML2 as shown in Table 8. The value of WTP is obtained as the ratio of the RM-centric attribute's coefficient relative to the fare coefficient. For instance, the mean WTP for departing from off-peak to peak periods, which is calculated as $-(5.758/-0.021) = \$274$ (local currency). More specifically, passengers are willing to pay extra $274 dollars (full fare is $2640 dollars for the studied market) in order to fly their schedules during peak hours. Even for those flights departing during the general period, passengers are willing to pay extra $123 dollars in comparison with those flights departing during off-peak hours. For having the flexibility of booking late, passengers are willing to pay $ 286 dollars and $159 dollars for being able to reserve within 14 days and 15–30 days before the flight take off, respectively. In other words, if operators aim to attract passengers for very early booking (31–60 days before departure), they have to provide $286 dollars fare deduction in order to attract passengers' attention. Regarding ticket validity, passengers are willing to pay $286 dollars and $131 dollars for having twelve-month and six-month period of ticket usage, respectively. In addition, free of charge and 10% penalty while requiring itinerary changes deserves $182 and $101 dollars, respectively. Last but not least, passengers are also willing to pay $ 69 dollars for having the flexibility of getting 90% refund.

Based on the values in Table 8, it is interesting to know that booking time and ticket validity are equally important which shares approximate WTP values and followed closely by departure time. Changing fees and refund are relatively less influential. As a result, booking time, ticket validity, and departure time can be regarded as the major fences while changing fees and refund can be taken as the second-tier fences on the design of booking classes.

4.4. Managerial implications

The aim of this study is to investigate how to structure booking classes described by prices and fences. With such information on hand, airline operators may be able to manipulate the content of booking classes to attract passengers' attention and conduct demand management strategies. Based on the WTP information in Table 8, a fare table with different combinations of fences and fares can then be generated. In order to introduce the derived fare table with booking classes, the full fare in operation of a domestic market is taken as an example to calculate the discounts of attribute combinations. Based on the result in Table 8, the overall number of fence combinations is one hundred and sixty two ($3 \times 3 \times 3 \times 3 \times 2 = 162$). In the following, only few cases are illustrated to show how to obtain the content of the derived fare table. Since full fare should be applied to a ticket with the loosest combination of fences, we first need to change the base of WTP for straightforward interpretation. The column of WTP* in Table 8 as a result shows the opposite version to explain WTP values. First of all, departing during peak hours is regarded as the first fence and consequently extends the table in terms of the other four fences. On the left hand side in Fig. 2, if booking within fourteen days is taken as the second fence, then there will be no any discount since it is the loosest restriction. Nevertheless, if one more fence is included such

Table 7
Results of mixed logit model.

	ML1		ML2		MNL	
	Coefficient	t value	Coefficient	t value	Coefficient	t value
Constants for alternatives						
Kiosk	0.979**	4.813	1.043**	5.092	0.249**	3.326
Online travel agency	0.165	1.062	0.186	1.160	0.387**	5.862
Departure time (General)						
Mean	2.472**	3.711	2.587**	3.479	−0.193	−0.930
SD	0.156	0.102				
Departure time (Peak)						
Mean	5.494**	4.249	5.758**	4.049	0.155	0.387
SD	0.733	0.841				
Booking time(15–30 days)						
Mean	3.197**	4.656	3.331**	4.537	0.299	1.443
SD	0.883	1.187				
Booking time (Within 14 days)						
Mean	5.789**	4.470	6.010**	4.270	0.480	1.206
SD	1.898**	3.595	2.235**	4.618		
Validity (1 month)						
Mean	−5.759**	−4.427	−6.016**	−4.205	−0.307	−0.760
SD	1.158*	1.724	1.898**	3.276		
Validity (6 months)						
Mean	−2.644**	−4.132	−2.760**	−3.915	−0.055	−0.264
SD	1.355**	1.981	1.354*	1.855		
Changing fee (10% ticket price)						
Mean	2.019**	5.575	2.121**	5.728	0.470**	4.337
SD	0.345	0.258				
Changing fee (Free of charge)						
Mean	3.552**	5.405	3.817**	5.290	0.724**	3.865
SD	1.544**	2.329	1.592**	2.419		
Refund percentage (90% refund)						
Mean	1.453**	4.383	1.453**	4.807	0.223**	2.271
SD	0.768	0.866				
Fare						
Mean	−0.021**	−5.449	−0.021**	−5.328	−0.003**	−2.980
SD	0.006**	4.784	0.006**	3.786		
LL(B)	−2260		−2264		−2300	
LL(const)	−2580		−2580		−2580	
LL(0)	−2623		−2623		−2623	
ρ^2	0.138		0.137		0.123	

Table 8
Willingness-to-pay of the fences (ML2 model).

	WTP	WTP[a]
Departure time		
Off-peak	0	−274
General	123	−151
Peak	274	0
Booking time		
31–60 days before departure	0	−286
15–30 days before departure	159	−127
Within 14 days before departure	286	0
Validity		
1 month	0	−286
6 months	131	−155
12 months	286	0
Changing fee		
Cannot be changed	0	−182
10$ ticket price	101	−81
Free of charge	182	0
Refund		
No refund	0	−69
90% refund	69	0

[a] WTP values if the base changes to the loosest fence.

as six-month ticket validity, then passengers expect to get 6% off the full fare ($2640-$155 = $2485). If the procedure is continued and the fence of paying 10% of ticket price for itinerary change is included, then the price will be 9% off the full fare ($2485-$81 = $2404). Ultimately, if no refund is added as the last fence, then passengers totally expect to have 12% off the full fare ($2404-$69 = $2335).

On the right hand side in Fig. 2, another example with much more strict fences can be observed. That is the ticket which needs to be booked 31–60 days before departure, one-month ticket validity, itinerary change prohibition, and no refund while announcing cancellation. By accepting such a combination of strict fences, passengers do expect to get 31% off the full fare ($2640-$286-$286-$182-$69 = $1817). By using the similar concept, Figs. 3 and 4 start from departing during general and off-peak periods as the first fence and further reveal more cases in terms of the combinations of fences, respectively. In the situation which passengers choose to depart during general hours (Fig. 3), the cheapest ticket passengers expect to get is 37% off the full fare ($2640-$151-$286-$286-$182-$69 = $1666). If passengers can even depart during the off-peak period (Fig. 4), then they expect to have 42% off the full fare for the ticket with the lowest price ($2640-$274-$286-$286-$182-$69 = $1543).

5. Conclusions

This study contributes to the literature by addressing the issue of how to obtain a demand-oriented fare table in the context of revenue management and partially fills the research gap of price framing indicated by Guillet and Mohammed (2015). By giving an identical seat service, this study aims to reveal how passengers

	Fare classes								
	2640 No discount								
First fence: Departure time	**Peak**								
	2640 No discount								
Second fence: Booking time	< 14 days			15~30 days			31~60 days		
	2640 No discount			1513 5% off			2354 11% off		
Third fence: validity	12 months	6 months	1 month	12 months	6 months	1 month	12 months	6 months	1 month
	2640 No discount	2485 6% off	2354 11% off	2513 5% off	2358 11% off	2227 16% off	2354 11% off	2199 17% off	2068 22% off
Fourth fence: Changing fee	Free	10%	Prohibit				Free	10%	Prohibit
	2485 6% off	2404 9% off	2303 13% off				2068 22% off	1987 25% off	1886 29% off
Fifth fence: refund	90%	No refund						90%	No refund
	2404 6% off	2335 12% off						1886 29% off	1817 31% off

Fig. 2. Fare table with corresponding fences (depart during peak hours).

	Fare classes								
	2640 No discount								
First fence: Departure time	**General**								
	2489 6% off								
Second fence: Booking time	< 14 days			15~30 days			31~60 days		
	2489 6% off			2362 11% off			2203 17% off		
Third fence: validity	12 months	6 months	1 month	12 months	6 months	1 month	12 months	6 months	1 month
	2489 6% off	2334 12% off	2203 17% off	2362 11% off	2207 16% off	2076 21% off	2203 17% off	2048 22% off	1917 27% off
Fourth fence: Changing fee	Free	10%	Prohibit				Free	10%	Prohibit
	2334 12% off	2253 15% off	2152 18% off				1917 27% off	1836 30% off	1735 34% off
Fifth fence: refund	90%	No refund						90%	No refund
	2253 15% off	2184 17% off						1735 34% off	1666 37% off

Fig. 3. Fare table with corresponding fences (depart during general hours).

make their choices of booking classes in terms of RM-centric attributes and shows the trade-off effect among fares and fences. First of all, the modelling results of MNL do not show satisfactory outcomes and such unexpected results may come from the violation of IIA assumption in MNL. With the use of ML model, all the applied fences including departure time, booking time, ticket validity, changing fee, refund, and fare are shown to have significant influences. Secondly, this study also considers the phenomenon of passenger heterogeneity toward the same seat service. The utilization of ML model can provide standard deviation information of the attributes. This study also reveals that heterogeneity does exist in the fences of booking time, ticket validity, changing fee, and fare. Passengers do possess different attitudes on these fences. Overall speaking, the mixed logit model may fit the data well and obtain more plausible estimation than the multinomial logit model. Thirdly, by combining the five studied fences, this study demonstrates how to generate one hundred and sixty two booking classes with corresponding fences/fares and provides a fare table for practice use.

For an airline company, it is crucial for operators to effectively utilize perishable seat resources to avoid either selling too many seats to passengers who possess low WTPs or having too many vacant seats while taking off. In order to do so, controlling the availability of booking classes become a critical management work. Through the investigation of fare structure from the demand perspective in this study, airline operators now will be able to have their customized fare table. Moreover, since the air market is very competitive with many substitutions, providing diversified seat products with various fares becomes essential to attract attentions from passengers in multiple market segments. Nevertheless, in order to prevent the situation of spillover which passengers transfer from high priced segments to low priced segments, the use

	Fare classes								
	2640 No discount								
First fence: Departure time	**Off-peak** 2366 10% off								
Second fence: Booking time	< 14 days 2366 10% off			15~30 days 2239 15% off			31~60 days 2080 21% off		
Third fence: validity	12 months 2366 10% off	6 months 2211 16% off	1 month 2080 21% off	12 months 2239 15% off	6 months 2084 21% off	1 month 1953 26% off	12 months 2080 21% off	6 months 1925 27% off	1 month 1794 32% off

Fourth fence: Changing fee	Free 2211 16% off	10% 2130 19% off	Prohibit 2029 23% off	Free 1794 32% off	10% 1713 35% off	Prohibit 1612 39% off

Fifth fence: refund	90% 2130 19% off	No refund 2061 21% off	90% 1612 39% off	No refund 1543 42% off

Fig. 4. Fare table with corresponding fences (depart during off-peak hours).

of fences become indispensable and the results of this study may shed light on the use of prevailing fences.

There are several extensions possible for further studies in the future. First of all, this study regards a domestic route as an example to show how to generate a fare table. Similar concept and framework can be applied to the international market to reconfirm the significance of the applied attributes and their corresponding WTP values. Secondly, other service-related attributes such as seat comfort, lounge service, and baggage fees (Teichert et al., 2008; Wen et al., 2009; Scotti and Dresner, 2015) or user-generated content such as ranking and review (Herrero et al., 2015; Noone and McGuire, 2014) can be integrated for further investigation. Thirdly, the proposed concept can also be extended to other transportation fields such as cruise (Sun et al., 2011) and parking (Guadix et al., 2009) to explore the influence of different types of fences. Last but not least, the developed model can be incorporated into a revenue optimization problem for seeking the optimal resource allocation (Hetrakul and Cirillo, 2014).

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