Fare Discounts and Purchase Restrictions: Trade-off Effects of Intercity Bus Passengers in Taiwan

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Abstract: This study aims to address trade-off effects among fares and fences by using sampling data from an intercity bus corporation. We first regard departure time, booking time, pay time, percentage of refund, and prices as major attributes that passengers bare in minds while making their ticket choices. 400 stated-preference questionnaires are distributed on bus while passengers are having their trips. We utilize mixed logit model to verify the importance of the proposed five attributes. The results show that all variables except pay time are significant at 95% confidence level. We further calculate willingness-to-pay of attributes to reveal their monetary value. Departing during peak hours is the first priority for passengers while buying tickets following by advanced booking and percentage of refund. For the managerial application, this study suggests a demand-oriented fare table considering three fences and generating eight different classes of tickets.

Keywords: Intercity Bus Operation, Fares and Fences, Stated Preference, Mixed Logit Model, Revenue Management

1. INTRODUCTION

Maximizing revenues based on daily operations is a very fundamental and vital goal for managers to achieve. Transportation operators usually manipulate the concept of market segment and create seat-based differential services to attract passengers with different willingness to pay (WTP). For example, passengers may choose to purchase tickets on line at low prices but have to pay in advance with penalties for changing itineraries. On the other hand, passengers with less price sensitivity may purchase tickets at high prices with more information and expedite services. In general, maximizing revenues by selling perishable seats to various market segments with a carefully designed fare menu has already become the routine for airlines since 1970s. Such management concept is recognized as revenue management which aims to sell right products to right customers at right time with right prices (Smith et al., 1992). In order to successfully avoid selling too many seats to passengers who possess low WTP or having vacant seats while taking off, four pivots namely demand forecasting, seat allocation, overbooking, and pricing need to be implemented (McGill and Van Ryzin, 1999). Rannou and Melli (2003) simulate the impact of revenue management in the airline industry and find that 3% to 7% extra revenues can be obtained. Kimes (2005) also shows that the utilization of revenue management concepts may bring 0.5% to 3% extra revenues in the airline, hotel, and car rental industries. Nowadays the concept of revenue management has been widely applied in many other industries such as restaurants, health care attractions, cruise line, casinos, golf, etc (Chiang et al., 2007).

While practicing revenue management applications, preventing a situation called demand spillover which passengers transfer from high priced segments to low priced segments is important. Creating different combination of restrictions to form so-called fences is a useful tool and commonly seen nowadays to restrict customer migration across segments. For instance, hotels use advanced purchase, channels, minimum stay, refund penalty and others to set up their service alternatives. Based on detailed fare information for city-pair markets in the United States (USDOT[a], 2012), domestic airlines in the US may have various ticket fares even for a specific market. For example, fares of Dallas to Memphis may vary from $125 to $675 US dollars. Pricing, in fact, provides a basic framework for airlines to segment the market and for passengers to reserve their preferred seats in terms of their requests. More specifically, for an airline seat, different types of passengers may have different valuation of seats which provide the base for deploying market segmentation and differential pricing (Zhang and Bell, 2012). In order to generate different seat-based services to attract distinctive market segments and avoid the situation of spillover, airline managers purposely add restrictions (or fences) which are rules that a company uses to determine who gets what price and can be used to help differentiate one transaction from another onto the seat (Kimes and Wirtz, 2003). For example, advance discount purchase (early bird) is applied to attract the segment which is time flexible with limited budget. In order to successfully implement revenue management, airlines ultimately need to possess a fare menu showing trade-off effects among fares and fences.

Many papers in the literature discuss about how to determine the optimal allotments of seat-based products in terms of demand fluctuation given a predetermined fare menu (Littlewood, 2005; Talluri, and Van Ryzin, 2004; Belobaba, 1987). On the other hand, other papers show how to calculate the shadow price of a seat as a reference price to accept or decline a new request (Chen and Freimer, 2004; Anderson, 2008). Some researchers focus on the issue of price presentation (Noone and Mattila, 2009; Rohlfs and Kimes, 2007; Parsa and Njite, 2004) and price determinant (Lee, 2011; Hung et al., 2010); however, relatively few papers address the issue of how to design a fare menu regarding purchasing fences. This study aims to fill this gap and calculate WTP of intercity bus services with different constraints. We will use sampling data from an intercity bus company as an empirical case to show how to obtain WTP values of fences. In the next section, we will first review related works in the literature from both empirical and theoretical aspects. The third section describes the methodology and procedures for sample collection. The results of multinomial logit and random parameter (mixed) logit models are presented and WTP values are shown to generate a customer-oriented fare menu in the forth section. Finally, conclusions with managerial applications are presented and suggestions are provided for future research.

2. LITERATURE REVIEW

Companies with perishable goods or services may deploy different price-setting strategies to attract clients from different market segments. In the airline industry, the general trend of fare is moving upward as the date is approaching the departure day (Bilotkach et al., 2010). The report of "getting the best airline fares" published by USDOT (USDOT[b], 2012) recognizes the upward phenomenon and suggests passengers planning their trips as far ahead as possible in order to get cheap tickets from the time-varying pricing scheme.

Although different types of customers may regard one specific service with distinctive values and are willing to pay different prices as a consequence, maintaining perceived fare fairness for provided services is critical and also the very first issue for operators while practicing differential pricing. If customers perceive differential pricing with fences as fair, they are more willing to accept the practice. However, it is not always the case especially in the beginning of the implementation. Wirtz and Kimes (2007) conduct an experiment to test the moderating role of similarity and found that framing and fencing condition have strong effects on perceived fairness when customers are less familiar with a pricing practice. In order words, providing enough information for customers who are not familiar with revenue management practices to tell the difference of services is a critical activity. For the role of familiarity, Taylor and Kimes (2010) further conduct an experiment and confirm that familiarity with the revenue management practice, rather than provision of practice information and hotel brand class, is the most important factor affecting perceived fairness. The finding implies that educating customers to understand how revenue management works is beneficial for operators to carry out related management activities. As a result, operators need to have a clear view about how to differentiate and sell their services in order to prompt the practice.

Fences are rules for a company to add onto services so that customers may self-segment on the base of their WTP and, more importantly, can help operators effectively focus on consumers who are willing to accept restrictions in order to obtain discounts. Kimes and Wirtz (2003) survey customers from Singapore, Sweden, and United States for their opinions on different pricing schemes in restaurants and conclude that fencing can be a very effective tool to improve perceived fairness of demand-based pricing. For example, coupons, time of dining are perceived to be fair but table-location based pricing is regarded to be unfair in their study. Different types of fences can be applied in different fields. Zhang and Bell (2012) indicate that fences can be categorized into purchase pattern, product characteristics, and customer characteristics. More specifically, constraints such as booking time, purchase time, channel, payment method are related to purchase pattern and are widely applied in transportation and service industries. Product-characteristic based fences include product usage (such as ticket validity), alternation charge (refund or changing fees), transaction cost, service option (permission of same-day standby), and information vagueness (such as booking on priceline websites (Anderson, 2008)). Last but not least, demographic variables function more like customer-characteristic conditions such as age, group, budget, and loyalty. In another study, Wirtz and Kimes (2007) categorize rate 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.

Fences are accompanied by fare discounts. A rack fare or full fare is initially determined and then corresponding discounts are given in terms of the level of fences. Usually, strict restrictions come with heavy discounts, and vice versa. For example, “no refund” should have a deeper discount than “penalty of itinerary change”. To the best knowledge of the authors, the fence-based discounts are commonly determined based on the operators’ experiences or following market reference. Very few research papers focus on the issue. As a result, this study aims to figure out the relationships among fare discounts and fences in the context of revenue management. More specifically, this study aims to find out critical fences which influence passengers’ choices and calculate the WTP values of individual fences so that the aggregation of fence-based WTP may yield the fare menu. The fare menu can show the trade-off effect among fares and fences and is very helpful for companies to communicate with customers about the differences of their services.

On the issue of calculating WTP of fences, regression and logit models are potential techniques. Reynisdottir et al. (2008) surveyed tourists who visit natural attractions and ask for their WTP of entering the attraction. They used a regression model to show the relationships between WTP and influential factors. Discrete choice model such as multinomial logit model (MNL) and mixed logit model (ML) are capable of figuring out how passengers make their selection from several alternatives. In the logit model family, MNL is the most widely applied method; however, MNL assumes that all alternatives are independent (independence of irrelevant alternatives, IIA) and recently more advanced and flexible ML has been applied. Wen et al. (2009) utilize MNL and ML to investigate how passengers choose airlines of a specific air route. Based on the modelling results and corresponding WTP values of preferred departure time, flight frequency, punctuality, check-in service, seat comfort, and cabin service, they conclude that passengers are willing to pay more for long-distance travel and service quality attributes. Balcombe et al. (2009) applies ML model to compute consumer WTP for in-flight service (meal, entertainment, drinks) and comfort levels (seat pitch and seat width). In short, they conclude that in principle passengers are willing to pay a relatively large amount for enhanced service quality. Garrow et al. (2007) applies MNL and nested logit model to find out WTP values for flying by air and also service improvement factors. They conclude that business passengers with high values of time are more likely than leisure travelers to purchase air travel and more willing to pay for improved service. In this study, we construct both MNL and ML to analyze passengers' choices and find out WTP of applied fences.

3. METHODOLOGY

3.1 Stated Preference Experiments

Stated preference experiments aim to test responses of interviewees given assumed attributes with corresponding levels. In other words, the benefit of stated preference experiments is to evaluate passengers' responses while facing different hypothetical scenarios. This study takes the advantage of the method to observe how passengers choose between fares and fences by using an intercity bus company as a case. We first design a hypothetical questionnaire to show the trade-off effects among fares and fences. Five main attributes utilized in this study are departure time, booking time, pay time, refund, and fare. The utilization of departure time is straightforward since peak/general/off-peak differential fares are prevailing and accepted by passengers in practice. For the studied case, the company currently divides the whole schedule into three different departure periods with corresponding prices (peak, general, off-peak). The second attribute is booking time which is the time point where passengers make their reservations during the booking period. For the studied case, it opens for reservations two weeks before departure. In this study, we divide the whole booking period into three sequences which are booking on departure day, booking 1~7 days before departure, and 8~14 days before departure, respectively. Usually, early booking (or so-called early bird) reduces the uncertainty for the company and obtains a discount as a reward.

The third attribute is pay time which can be regarded as a kind of alternation cost. If passengers have already paid in advance, they will have a transaction cost when they decide to change or even cancel the booking. On the contrary, if passengers do not need to pay in advance, they may cancel, change, or rebook easily without any extra cost or penalties. In this study, we divide the whole pay time into four sequences: pay immediately after booking, pay after booking and 7 days before departure, pay after booking and one day before departure, and pay on the departure day. The combination of booking time and pay time should have a temporal sequence since it is impossible to pay first before booking. Regarding the discount, pay-in-advance may reduce the uncertainty of demand and should obtain a discount as a reward. The forth attribute is refund which is also very prevailing in airlines, hotels, and other service industries. Refund can be seen as a sort of switching cost. As a result, deploying a refund constraint can prevent passengers from transferring to other competitors or substitute modes. In this study, we provide three hypothetical scenarios which are refund 100%, 90%, 80%, respectively. If passengers want to have more refunds, they should expect to pay more while booking.

Each scenario is the combination of attributes and has a corresponding discount as a consequence. We have a thorough face-to-face interview with the management team of the studied company to obtain suitable discounts of different levels of attributes in Table 1. The combination of various attributes may yield an aggregated discount which influences the applied fare. For example, if a ticket which departs at off-peak, book 6 days before departure, pay immediately after booking, and expect to have 80% refund, the aggregated discount of it would be $0.8 \times 0.9 \times 0.9 \times 0.9 = 0.5832$.

For an intercity bus corporation, seat-based differential services may be obtained depending on the combination of the attributes and their levels in Table 1. Since booking time and pay time has a sequential relationship, we may yield three hypothetical alternatives correspondingly for passengers to choose, as shown in Table 2. We should emphasize that in our country if passengers pay at the cash counter, most of them expect to have all refund back if they desire to cancel their trips on the spot. In addition, explaining the content of individual fences and their accompanied discounts is also not possible while many customers are waiting in line. We consider this country specific effect into the experiment design by assuming that if passengers pay on departure day, they would have all money back if they cancel the trip. As a result, we may generate all possible experiments showing the trade-off relationships among fares and fences. However, it is impossible to conduct a full factorial experiment since it has 2×3^7 experiments. In this study, we implement a fractional factorial design by utilizing the orthogonal table $L_{18}(2 \times 3^7)$. As a result, only 18 experiments need to be tested and each questionnaire contains three independent experiments for respondents to answer.

Table 1 Attributes, levels, and corresponding discounts

Attribute	Level	Discount
Departure time	Off-peak	0.8
	Peak	1.0
	General	0.9
Booking time	Departure day	1.0
	1~7 days before departure	0.9
	8~14 days before departure	0.8
Pay time	Pay immediately	0.9
	Pay after booking and 7 days before departure	0.9
	Pay after booking and 1 day before departure	0.95
	Pay on departure day	1.0
Refund	No refund	1.0
	90% Refund	0.95
	80% Refund	0.9

Table 2 Alternatives, attributes, and levels

Alternative	Departure time	Booking time	Pay time	Refund	Discount
A	Peak General Off-peak	Departure day 1～7 days before departure 8～14 days before departure	Departure day	100% Refund	Calculate from Table 1
B	Peak General Off-peak	1～7 days before departure	Immediate after booking After booking ~ 1 days before departure	100% Refund 90% Refund 80% Refund	Calculate from Table 1
C	Peak General Off-peak	8～14 days before departure	Immediate after booking After booking ~ 1 days before departure After booking ~ 7 days before departure	100% Refund 90% Refund 80% Refund	Calculate from Table 1

3.2 Mixed Logit Model

The investigation of this study utilizes a stated preference questionnaire, which includes hypothetical scenarios to which the participants are expected to respond in one experiment. The questionnaire requests the interviewees to make a choice from a set of alternative services which are described by five introduced attributes. Then utility for each alternative service can be calculated and the choice probability of each service can be formulated by Mixed logit model (ML). The core of ML model follows its original MNL derivation which aims to maximize utility while making the choice. Essentially, each alternative in the model has a corresponding utility function which is composed of systematic and random error components. Instead of assuming estimated parameters are constant over passengers, ML models allow parameters to vary over passengers with density function $f(\beta|\theta)$. The ease of constant parameter makes ML more flexible than MNL and can deal with heterogeneity among passengers. In most applications, ML models adopt 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 is described as Equation (1) where β_{it} are random parameters, X_{it} is a vector of collected variables, and ε_{it} has independent and identical distribution of error terms. If the error terms are assumed to follow an independent and identical Gumbel distribution, the unconditional probability of choosing alternative *i* is the integral of the conditional probability with MNL form over β of density function $f(\beta|\theta)$ as shown in Equation (2). 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.

$$U_{it} = \beta_t{}' X_{it} + \varepsilon_{it} \tag{1}$$

$$P_{it} = \int \left(\frac{\exp(\beta'^{X_{it}})}{\sum_{j=1}^{J} \beta'^{X_{jt}}}\right) f(\beta|\theta)\, \mathrm{d}\beta \tag{2}$$

3.3 Data Collection Procedure

The designed stated questionnaire consists of three major parts. The first part asks for actual purchase behaviours for the trip while conducting the survey. The second part requests socioeconomic characteristics of the respondents. The last part of the questionnaire contains hypothetical scenarios for respondents to answer and each questionnaire has three scenarios. Each scenario is composed of three alternatives described by five attributes. The studied trip is a long-haul journey during the weekend (from Friday to Sunday). Population is targeted to be the current customers of the studied company who are above 18-year-old. The sampling process is implemented on the bus while passengers are using the service. In addition, we follow the concept of random sampling while picking up respondents on the bus. The survey is conducted from Friday to Sunday for three consecutive weeks in January 2012. All respondents are required to evaluate three randomly drawn choice tasks. Finally, four hundred valid samples are obtained and unfinished questionnaires are the only reason for invalid samples in the survey.

As indicated in Table 3, the collected samples consist of 60% male passengers; the 18~30 year-old group composes 71% of the samples; 38% are students and 56% are working people; 73% of the samples possess college degree and above; 74% of the respondents make monthly income less than 40k. In order to make sure that the composition of the profile is close to the market situation, we compare the demographic features with another domestic study (Hu, 2008) and confirm the representation of the profile. The actual purchase behaviors also show that 35% of the samples are having home-based trip; 65% of them book and pay on the departure day; 6% of them book in advance but pay on the departure day.

Table 3 Profiles of respondents

Gender	%	Eduction	%
M	60	Junior	2
F	40	Senior	15
		University	65
		Postgraduate	18
Age			
18~30	71	Monthly income	
31~40	16		
41~50	9	<10k	29
51~60	3	10k~20k	13
>61	<1	20k~30k	16
		30k~40k	16
		40k~50k	10
Occupation		50k~60k	8
Student	38	60k~70k	2
Public sector	16	>70k	4
Service industry	14	Frequent flier	
Industrial	10		
Business	9	Entrant	55
Self-employed	6	Medium	22
Others	6	High	7
		Loyal	16

4. EXPIRICAL RESULTS

4.1 Results of Mixed Logit Model

In order to run the mixed logit models, we first transform the attributes into numerical codes including four qualitative service attributes and one quantitative fare variable. For departure time, the base is set to be off-peak (0,0); peak is represented by (1,0) and general is (0,1). For booking time, the base is set to be departure day, 1~7 days before departure=(1,0) and 8~14 days before departure=(0,1). For pay time, the base is pay immediately after booking=(0,0), pay after booking and 1 days before departure=(0,1), pay after booking and 7 day before departure=(1,0), and pay on departure day=(1,1). Refund has also similar setting where the base is 100% refund=(0,0), 90% refund=(1,0), and 80% refund=(0,1). The aggregated discount is then calculated by using Table 1 and then the number is multiplied by the full fare to generate final fare which customers receive. All the five attributes are specified as generic variables with two alternative specific variables.

The estimation results of the ML model are summarized in Table 4 with MNL outcomes for comparing purposes. As expected, the proposed five attributes are all significant at 95% confidence level except pay time. Several interesting findings are summarized as below. First of all, Table 4 shows that departing during peak hours increases utilities since passengers may arrive at their preferred time. Early arrivals and late departures to non-peak periods both decrease utilities. Booking within 7 days before departure in fact does not decrease utility; however, if passengers have to make their reservations more than 8 days before departure, utility will then significantly decrease as a consequence. Regarding the result of pay time, ML shows no significance while MNL indicates positive effect on utility if passengers pay 1~7 days before departure. In fact, MNL results do not reflect reality since most passengers desire to pay at last minute so that they may maintain the most control of their trip. The conflict outcome of MNL may be caused by the assumption of parameter homogeneity which is embedded in MNL. For the refund constraint, passengers prefer to have all their money back if they desire to change or cancel their trips. For the percentage of refund, having less refund back will decrease utility. In addition, the utility decrease due to the first 10% penalty (90% refund) is much larger than that of the second 10% penalty. Last but not least, fare has a significant negative effect on utility which echoes the real situation.

Table 4 Results of Logit Models

	ML model		MNL model	
	Coefficient	t value	Coefficient	t value
Constants for alternatives				
Alternative A	1.23*	3.72	0.91*	4.23
Alternative B	-0.37	-1.28	-0.18	-0.97
Departure time (Peak)				
Mean	2.58*	2.29	2.03*	2.96
SD	1.87*	2.17		
Departure time (General)				
Mean	0.28	0.86	0.17	0.78
SD	0.05	0.05		
Booking time (1~7 days)				
Mean	0.17	0.50	0.10	0.39
SD	1.16*	2.36		
Booking time (8~14 days)				
Mean	-1.87*	-2.34	-1.35*	-2.67
SD	0.15	0.23		
Pay time (Booking~7 days)				
Mean	-0.27	-1.16	-0.13	-0.81
SD	0.26	0.24		
Pay time (Booking~1 days)				
Mean	0.39	1.93	0.36*	2.62
SD	0.19	0.26		
Refund (90%)				
Mean	-1.04*	-2.70	-0.48*	-3.16
SD	2.11*	2.86		
Refund (80%)				
Mean	-1.14*	-2.91	-0.68*	-3.00
SD	0.45	0.28		
Fare	-0.02*	-2.65	-0.01*	-3.24

* Significance level is 5%

4.2 Willingness-to-pay of Attributes

In the following, we calculate WTP of each attribute to quantify its monetary value as shown in Table 5. First of all, passengers may pay extra 143 NT dollars (full fare is 710 NT dollars; 1 USD=30 NTD) in order to ride on their desire schedules during peak hours. In addition, the WTP difference between off-peak and general hours is not large (only 16 NTD). Second, if the operator aims to attract passengers for very early booking (8~14 days before departure), it should provide 103 NTD fare deduction. Since booking 1~7 days before departure day does not decline utility significantly, the WTP difference between pay on departure day and pay 1~7 days before departure is small (9 NTD). The circumstance suggests that two types of booking time should be good enough for segmenting passengers. Third, the fence of pay time is not treated as a critical fence. As a result, the fence of pay time is neglected in the following discussion and implication. Forth, if the operator wants to draw refund constraints, he/she should provide 57 NTD reduction for 90% refund and another 6 NTD deduction for extra 10% penalty.

Table 5 Willingness-to-pay of attributes by the ML model

Departure time	
Off- peak	0
General	16
Peak	143
Booking time	
Departure day	0
1~7 days before departure	9
8~14 days before departure	-103
Pay time	
Pay immediately	0
After booking & 7 days before departure	-15
After booking & 1 day before departure	22
100% Refund	0
90% Refund	-57
80% Refund	-63

4.3 Managerial Implication

This study aims to investigate how intercity bus passengers make their ticket choices regarding the trade-off effects among fares and fences. The empirical modelling results first show that departure time is crucial for passengers since it affects their preferred arriving time zones. Nevertheless, Table 4 indicates the insignificance of the general-hour category which suggests the operator adopting peak/non-peak hours rather than three departure time zones (peak/general/off-peak). Second, Table 4 also reveals that booking within a week does not necessarily decrease passengers' utilities. Currently, almost 65% of the company's passengers make their ticket choices on departure day and such a phenomenon may increase difficulties of demand management in daily operations. Since reservation may help passengers feel seat secure on one hand, it also provides ample information for operators to implement demand management strategies. As a result, the company should provide discount-free incentives to encourage passengers to book within a week before departure. For instance, communicating the benefit of reservation with passengers or providing limit edition of souvenirs are common ways to attract attention. If further encouragement of booking beyond 7 days (and more) is expected, discounts will be appealing. The percentage of refund negatively affects passengers' utilities. More important, the first 10% penalty (or 90% refund) seems to be a much higher fence than the second 10% penalty. This outcome implies the nonlinear effect of the refund fence. As a result, careful use of this fence in practice is necessary since the effect is marginalized as the percentage of penalty increases. If the effect of a fence is not large enough, the use of it would only increase the complexity of the fare menu and confuse customers.

Based on Table 5 and the full fare, we may calculate the price of all attribute combinations at different levels. It should be emphasized that since the fence of pay time is not critical, here the calculation ignores this fence. In addition, we also limit our illustration without showing the impact of departing at general hours since the WTP difference between off-peak and general hours is only 16 NTD. We do not aim to show the influence of 80% refund as well since the WTP difference between the first 10% penalty and the second 10% penalty is rather small (6 NTD). Table 6 shows eight fare classes depending on the combination of different levels of attributes and results in various prices ranging from 407 NTD (43% off) to 710 NTD (full fare). In reality, the studied company currently only applies the first fence. With the findings of this study, the operator may consider to extend their fare menu to contain at most eight different types of seat-based services. Passengers who possess different WTP towards provided services will select suitable services to satisfy their own requests. For example, students who are usually time flexible with high price sensitivity would select the fare class with the highest fence (and lowest fare). On the other hand, business clients may select the fence-free fare class since their schedule is usually tight and price sensitivity is also low.

Table 6 Fare table with corresponding fences (including discount information) unit: NTD

	Fare classes							
Full fare	710 No discount							
First fence: departure time	Peak hours				Non-peak hours			
	710 No discount				567 20% off			
Second fence: booking time	within a week		8~14 days before departure		within a week		8~14 days before departure	
	710 No discount		607 15% off		567 20% off		464 35% off	
Third fence: Refund	100%	90%	100%	90%	100%	90%	100%	90%
	1 710	2 653	3 607	4 550	5 567	6 510	7 464	8 407
	No discount	8% off	15% off	23% off	20% off	28% off	35% off	43% off

In Taiwan, high speed railway, conventional railway, flight, and cars are four major substitutes for the mode of intercity bus which used to be a very prosperous market in the last decade. However, the commercial operation of high speed railway has attracted a significant number of passengers who care more about time rather than prices. The competition within the industry has become more and more fierce. Even for the intercity bus market, four corporations are currently running business in the studied market. Luxury seat comfort, on-board personal entertainment system, free water, and high frequency are major tools to differentiate homogenous transportation service. Revenue management, which aims to allot the optimal number of seats given a fare structure, has been proved to be a killer application back in 1970s in the airline industry (Cross, 1997). The structure of the fare menu is usually based on supply side or simply following the market leader rather than on demand side. The contribution of this study is to propose a demand-oriented design of fare structure and hopes the modelling results can provide useful information for applying revenue management in the intercity bus industry. Given a pre-determined multi-segment fare menu, the operator may start forecasting arrivals and allotting seat resources for each fare class in order to maximize revenues.

5. CONCLUSIONS

This study addresses on how to generate a demand-oriented fare table in the context of revenue management and reveals the trade-off effect among fares and fences. The modelling results confirm the importance of the proposed fences and three out of four fences such as departure time, booking time, and refund percentage are regarded to be significant while making ticket choices. More specifically, departing during peak hours obtains the largest willingness-to-pay which shows its priority in passengers' minds, following by very early bird reservation (8~14 days before departure) and how much money passengers can get back if they cancel the trip. For the studied case, this study also shows that the currently applied three-time-zone schedule can be simplified to a two-time-zone schedule. In addition, we also consider the use of all three fences and render a sophisticated fare table containing eight differential service products for revenue management applications.

There are several extensions available for further investigation in the future. First of all, the simulated revenue impact can be computed if applying the suggested fare table in the company so that the benefit of using the suggested fare table can be justified with evidences. Second, researchers may investigate the trade-off effects of other possible fences such as minimum tickets to buy or ticket validity. In addition, the integration of fences with service improvements such as seat comfort or non-stop service can be discussed together. Third, the proposed concept can be extended to other industries such as airlines, railway, cruise, and car rentals.

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