TRADE-OFF EFFECTS AMONG DISCOUNTS AND FARE RESTRICTIONS: A CASE STUDY OF AN INTERCITY BUS CORPORATION

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ABSTRACT

This study aims to figure out the trade-off relationships among discounts and fare restrictions 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 trip decisions. 400 stated-preference questionnaires are distributed on bus while passengers are having their trips. We utilize multinomial logit models to verify the importance of the aforementioned five attributes and the results show that all five variables are significant at 95% confidence level. This study further calculates willingness-to-pay of departure time, booking time, pay time, and percentage of refund to reveal their monetary values and priority in passengers' minds. More specifically, be able to depart during peak hours is the most important thing for bus passengers since the attribute has the largest willingness-to-pay. Booking in advance actually has no harm to the utility if it is made within seven days before departure. Pay-in-advance in fact increases utility and corresponding choice probability. In addition, passengers as expected want all refund and do not like to pay penalty when they cancel the trip. This study finally suggests a fare table considering three common fences and generating 12 types of ticket. The core of revenue management is to sell right products to right customers at right time with right prices. With the proposed model, the operator now may have a demand-oriented fare table which is the combination of products and prices for the use in the context of revenue management.

Keywords: Intercity Bus Operation, Fare Fence, Stated Preference, Willingness-to-pay, Revenue Management

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INTRODUCTION

Having maximized revenues is a very fundamental and vital goal for managers to achieve. For airlines, maximizing revenues by selling perishable seats to various market segments with an elaborate fare menu has already become the routine since 1970s. Such management concept is called revenue management which aims to sell right products to right customers at right time with right prices (Smith et al., 1992). More specifically, four pivots need to be implemented in order to avoid selling too many seats to customers who possess low willingness-to-pay or having vacant seats while taking off. These four pivots are demand forecasting, seat allocation, overbooking, and pricing (McGill and Van Ryzin, 1999). A strong support of applying revenue management in real time is from Kimes (2003) who has shown that the utilization of revenue management concepts may bring 0.5% to 3 % extra revenues in the airline and hotel industries. Nowadays the concept of revenue management has been seen in many industries such as restaurants, health care attractions, cruise line, casinos, golf, etc (Chiang et al., 2007).

Pricing, in fact, provides a basic framework for passengers to reserve their preferred seats or services. 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 products/services to attract distinctive market segments and avoid spill over, airline managers purposely add restrictions or so-called 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. The manipulation and combination of fences may result in different products suitable for creating different market segments. In order to successfully implement revenue management, airlines ultimately need to possess a fare menu showing the trade-off effect between fences and prices in order to cope with different demand situations.

In the field of revenue management, 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, 2003; Belobaba, 1987). On the other hand, some other papers show how to calculate the shadow price of a seat as a reference to accept or decline a new request (Anderson, 2008). Some researchers focus on the issue of price presentation (Rohlfs and Kimes, 2007), price determinant (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 calculates willingness-to-pay (WTP) of 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 logit models are presented and WTP values are shown to generate a customer-oriented fare menu in the forth section. Finally, conclusions are presented and suggestions are provided for future research.

LITERATURE REVIEW

Industries such as airlines may deploy different price-setting strategies; however, the general trend of fare is increased as the date is approaching the departure day (Bilotkach et al., 2010) Different types of customers may regard one specific product/service with distinctive values and are willing to pay different prices as a consequence. However, for a specific service, how to keep perceived fairness when charging different prices in terms of different market segments has become a very first issue for revenue management applications. In order to maintain the perceived fairness, fences or constraints are usually imposed to create differences. Kimes and Wirtz (2003) argued that fencing can be a very effective tool to improve perceived fairness of demand-based pricing and surveyed restaurant customers five different fences across three countries. They found that coupons, time-of-day pricing, and lunch/dinner pricing are perceived fair without any country-specific effect. Wirtz and Kimes (2007) and Taylor and Kimes (2010) further proved that the whole revenue management ideas are perceived to be fair if customers are familiar with practices.

Different types of fences can be applied in different fields. Zhang and Bell (2012) summarizes fences as purchase pattern, product characteristics, and customer characteristics. Constraints such as booking time, purchase time, channel, method of payment are related to purchase pattern and are widely applied in airlines and hotels. 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 which are also common in the service industry. Last but not least, traditional segment variables function more like customer-characteristic conditions such as age, group, budget, and loyalty.

On the issue of how to calculate willingness-to-pay (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. Disaggregated choice model such as multinomial logit model (MNL) is also capable of figuring out how passengers made their selection and calculating WTP of attributes. MNL is the most prevailing model applied in the literature to discuss how people make their decisions while using service such as transportation mode choice (Wen et al., 2009) and wine purchase (Lockshin et al., 2006). Wen et al. (2009) applied MNL to discover how passengers choose airlines of a specific air route. Based on the modelling results, they compute WTP of attributes such as preferred departure time, flight frequency, punctuality, check-in service, seat comfort, cabin service, etc; these WTP numbers are very informative and can be regarded as the base to design the fare menu. The fare menu can show the relationships between fares and fences and is very helpful for improving perceived fairness since companies now have a list on hand to communicate with customers about the differences of their products.

METHODOLOGY

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 usage of departure time is straightforward since peak/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. 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 for the company 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 wants to have more refund, they should expect to pay more while booking.

Each scenario is the combination of attributes and has a corresponding discount. We have a thorough face-to-face interview with the management team of the studied company to obtain Table 1. The combination of various attributes will yield an aggregated discount. For example, if a ticket which departs at off-peak, book 6 days before departure, pay immediately, and expect to have 80% refund, the aggregated discount of it would be $0.7 \times 0.9 \times 0.9 \times 0.9 = 0.5103$.

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

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 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. 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 partial 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 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	Base on 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	Base on 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	Base on Table 1

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 multinomial logit model (MNL).
The core of MNL is random utility theory 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 (see Equation (1)). In Equation (1), V_{it} is the systematic component and usually defined by a linear function; X_{it} is a vector of collected variables describing the choice behaviour of product *i* for passenger *t*; ε_{it} is the error component and β is a vector of parameters associated with X_{it}. By assuming that errors in the utility functions follow independent and identical Gumbel Distribution can derive MNL. In short, given a set of *J* alternatives, MNL can specify the probability of passenger *t* choosing alternative *i* (see Equation (2)). All estimations are obtained by using NLOGIT software in this study.

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

$$P_{it} = \frac{\exp(V_{it})}{\sum_{j=1}^{J} \exp(V_{jt})} \tag{2}$$

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 and the last part of the questionnaire contains hypothetical scenarios for respondents to answer. Each scenario is composed of three alternatives described by five attributes. Background information of the studied trip is that it is a long-haul journey during the weekend (from Friday to Sunday). Population is set to be the current customers of the studied company and also 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. 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 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 behaviours 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以上	<1	20k~30k	16
		30k~40k	16
Occupation		40k~50k	10
		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

EMPIRICAL RESULTS

Results of MNL model

In order to run the multinomial logit models, we first transform the attributes into numerical codes including four qualitative and one quantitative variables. 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 7 days before departure=(0,1), pay after booking and 1 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 the number is multiplied by the full fare. All the five attributes are regarded to be generic variables with two alternative specific variables.

The estimation results of the MNL model are summarized in Table 4. As expected, the proposed five attributes are all significant at 95% confidence level with the interesting findings described as below.

First of all, Table 4 shows that departing during peak hours increases utility since passengers may arrive at their preferred time. 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 result. Regarding the effect of pay time, making payment in advance will not decrease utility. In fact, if passengers can make their payment 7 days before departure, utility can even be increased. 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 for sure. Last but not the least, fare has significant a negative effect on utility which just echoes the status quo.

Table 4 Results of Multinomial Logit Model

	Coefficient	t value
Constants for alternatives		
Alternative A	0.91*	4.23
Alternative B	-0.18	-0.97
Departure time		
Peak	2.03*	2.96
General	0.17	0.78
Booking time		
1~7 days before departure	0.10	0.39
8~14 days before departure	-1.35*	-2.67
Pay time		
After booking & 7 days before departure	-0.13	-0.81
After booking & 1 day before departure	0.36*	2.62
Refund		
90% Refund	-0.48*	-3.16
80% Refund	-0.68*	-3.00
Fare	-0.01*	-3.24

* Significance level is 5%

Willingness-to-pay of attributes

In the following, we calculate willingness-to-pay (WTP) of each attribute to quantify its influence. Table 5 lists WTP of different levels for individual attribute. First of all, the table indicates that passengers would like to pay extra 152 dollars (full fare is 710 dollars, local monetary) in order to get on the bus during peak hours. Second, if the company aims to attract passengers for very early booking (8~14 days before departure), it should provide $101 fare deduction. Third, passengers would like to pay 27 extra dollars in return for having the function of pay-in-advance. This outcome somehow reveals the benefit of having pre-paid mechanism for the studied company. Forth, if the company wants to draw refund constraints, it should provide 35 dollars reduction for 90% refund and 50 dollars deduction for 80% refund.

Based on Table 5 and the full fare (710 dollars), we may calculate the price of all attribute combinations at different levels. In order to simply the illustration, here we ignore the influence of pay time since this attribute has rather lower WTP values comparing with the rest attributes. In addition, we also limit our illustration without showing the impact of departing at general hours since WTP of this level is also small (13 dollars). Table 6 shows 12 fare classes depending on the combination of different attributes and results in various prices ranging from 407 dollars to 710 dollars. Currently, the studied company only applies the first fence and has 2 fare classes. In fact, it can further include the fence of booking time to increase the number of fare classes to from 2 to 4. Similarly, the company may utilize all three fences to generate a fare table including 12 different seat-based services.

Table 5 Willingness-to-pay of attributes

Departure time	WTP
Off- peak	0
General	13
Peak	152
Booking time	
Departure day	0
1~7 days before departure	7
8~14 days before departure	-101
Pay time	
Pay immediately	0
After booking & 7 days before departure	-10
After booking & 1 day before departure	27
Refund	
100% Refund	0
90% Refund	-35
80% Refund	-50

Table 6 Relationships among fares and fences

	Fare classes											
Full fare	710											
First fence: departure time	Peak hours						Off-peak hours					
	710						558					
Second fence: booking time	1~7 days before departure			8~14 days before departure			1~7 days before departure			8~14 days before departure		
	710			609			558			457		
Third fence: Refund	100%	90%	80%	100%	90%	80%	100%	90%	80%	100%	90%	80%
	[1] 710	[2] 675	[3] 660	[4] 609	[5] 574	[6] 559	[7] 558	[8] 523	[9] 508	[10] 457	[11] 422	[12] 407

Discussion

This study aims to figure out 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. However, Table 4 also indicates the insignificance of the general-hour category. As a result, the operator may consider simplifying the category of departure time by using peak/off-peak hours rather than three departure time zones (peak/general/off-peak). Second, Table 4 also reveals that reservation is not necessarily a negative thing for passengers since the estimator (0.10) is not different from zero in statistics. Based on the current situation, 65% passengers book and pay on the departure day which increase difficulties for demand management. The benefit of reservation mechanism is to help both passengers and the company by reducing uncertainty. On one hand, passengers can feel secure about being on board while departure after making reservations. On the other hand, the operator may expect to sell a certain number of seats before departure and arrange its capacity if necessary.

Pay-in-advance confirms the reservation further reduces demand uncertainty for the company. Table 4 shows that clients also prefer to pay a little bit early before departure since utility may be increased by doing so. The outcome implies the necessity of the pay-in-advance mechanism by different channels such as using credit or even by cash. Last but not least, the percentage of refund negatively affects the utility. 90% refund brings 0.48 reduction to the utility and 80% refund brings another 0.2 reduction to the utility. This outcome implies the nonlinearity of the refund effect which the effect of the first 10% penalty is larger than that of the second 10% penalty. As a result, careful use of this characteristic in practice is necessary since the refund effect is marginalized as the refund percentage increases.

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. In fact, there are four intercity bus corporations currently running business in the studied route. Luxury seat comfort and on-board entertainment are two 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 (Cross, 1997). However, the structure of fare classes is usually based on supply side rather than demand side. The value 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.

CONCLUSIONS

This study addresses on how to generate a demand-oriented fare table in the context of revenue management and reveals the relationships among discounts and fare restrictions. The results of this study confirm the importance of the studied fences such as departure time, booking time, pay time, percentage of refund, and prices while passengers are making their trip decisions. Furthermore, 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. Although willingness-to-pay of pay time is not relatively large in comparison with other fences, pay-in-advance can increase utility and should be a basic function for passengers in the intercity bus industry. For the studied case, the results also show that the currently applied three-zone-schedule can be simplified to two-zone-schedule. Based on these findings, the operator may have basic information to adjust its fare table in order to attract passengers' attention and improve revenues. For example, when demand is high, the operator should limit the use of low fare classes and vice versa. Furthermore, the results of this study provide a procedure to yield a series of seat-based service items with corresponding prices.

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 more evidences. Second, since logit model has some limitations such as independence of irrelevant alternatives (IIA) and homogenous assumption, researchers may try other advanced models such as nested logit model and mixed logit model to observe model performance. Third, the proposed concept can be extended to other industries such as airlines, hotels, and car rentals to test the willingness-to-pay of other fences.

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