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TOPIC 15
TRAVEL CHOICE AND
DEMAND MODELLING

MODELLING OF NEW PRICING STRATEGIES FOR THE SANTIAGO METRO

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Abstract

Our problem was to model the time-of-day choice of travel of people who would start facing a pricing system that charges differently depending on the period of the day. For this purpose, we used stated preference (SP) rating data, collected in December 1993 from users of the Santiago Metro (which had a flat fare system), on the willingness to change time of travel when offered a money discount and an improvement in comfort.

INTRODUCTION

The Santiago Metro, which has only two lines, has used a very simple pricing system since its foundation. However, this may have encouraged a strong increase in congestion during the peak hours in the last years.

The firm considered inadequate to increase supply at those hours to solve this problem, not only because of the high costs involved in buying new coaches, but also because it became obvious that most of this increase in supply would not be used during the rest of the day. Thus, it was decided to incorporate demand management policies in order to induce travellers to adjust their time of travel, flattening the demand and making it more even between the peak and off-peak hours.

The main aim of this paper is to model travellers' behaviour in order to predict their re-timing responses to fare changes and improvements in comfort. For this purpose we used stated preference (SP) data collected in September 1993, during a study that helped to decide the current time-of-day pricing strategy of the Santiago Metro which is operating since February 1994. The current system was also simulated using the best models estimated in order to test their general validity.

The rest of the paper is organized as follows. In the next section we describe the data in certain depth. The following section briefly presents the models estimated and the section after discusses the predictive performance of the best models using observed data for 1994. The final section summarizes our main conclusions.

EMPIRICAL DATA AVAILABLE

Description of the data

In this research we used data collected in a previous project carried out for the Santiago Metro by the Catholic University of Chile (DICTUC, 1993). The study was done in order to aid the design of the new pricing system so it was necessary to conduct a SP survey.

This exercise was conducted during the hours defined by Metro as the most congested in each peak period:

Morning Peak 7:30— 9:00

Evening Peak 18:00—19:30

Because of the crowds travelling at those periods a self-fill questionnaire which could be answered by the respondents at their offices or homes and returned to the Metro ticket offices was used. Also, each respondent was first asked to answer a short segmentation form regarding the characteristics of the trip they were making and their socio-economic characteristics. Both survey forms (SP and segmentation) were related by a unique record number. In order to ensure better results, the survey was carried out during both peak periods on Thursday the ninth of September by 61 interviewers who were last year university students. The number of interviewers per station was proportional to its patronage. Each student was assigned a specific station and platform.

The respondents had four days to return the SP survey to any Metro ticket office. To obtain a better response rate, not only a free ticket was offered but also a Ch$ 50,000 prize among all completed questionnaires (at the time 1 US$= Ch$ 420). Table 1 presents a summary of the response rate achieved; as it can be seen the global rate was 31.6 % and this was judged reasonably high.

Table 1 Response rates achieved

	LINE 1			LINE 2			TOTAL		
	Surveys Given	Surveys Returned	Response Rate (%)	Surveys Given	Surveys Returned	Response Rate (%)	Surveys Given	Surveys Returned	Response Rate (%)
Morning	792	274	34.6	451	160	35.5	1243	434	34.9
Evening	850	241	28.4	446	128	28.7	1296	369	28.5
TOTAL	1642	515	31.4	897	288	32.1	2539	803	31.6

The SP exercise consisted in presenting to the respondents one travel alternative similar to the trip they were making at that time ("current option"), and a second one which involved changing their time of travel to a less congested period ("off-peak option"). They were asked to indicate the option closer to their preference on a 5-point semantic scale:

1 I would definitively choose option A

2 I would probably choose option A

3 I would be indifferent between options A and B

4 I would probably choose option B

5 I would definitively choose option B

In order to minimize bias we decided to ask not only their time of travel but also information about any time restrictions that the travellers may had at their origin or destination. This information was asked during the segmentation exercise. According to their response, a SP survey was given to each traveller in which the off-peak option consisted in travelling before or after the peak period, depending on the case.

The SP design considered the following attributes:

i) Travel Cost, three levels (-Ch$ 10, -Ch$ 30 and -Ch$ 50); the travel cost presented to the respondent in the current option was that actually paid at the time of the survey (Ch$ 120). An exception was made when the off-peak discount offered was Ch$ 50; as it was judged that Ch$ 70 was too low a fare the current option price was raised to Ch$ 130 in that case.

ii) Waiting Time, two levels; this attribute was fixed in the current option but alternated in the off-peak option between being equal to, or one to one and a half minutes more than in the current option (for Lines 1 and 2 respectively). The questionnaire associated this variable to the train headways at each period.

iii) Comfort, three levels defined as follows:

- "Standing in very crowded conditions, sometimes you may have to wait for the next train in order to get in", this sentence was always associated with the current option.
- "Standing with some space"; this was the first level of improvement in comfort for the off-peak option.
- "With fewer people waiting for the train, so you may travel seated"; this was the second level of comfort improvement for the off-peak option.

Table 2 presents a summary of the different attribute levels considered in this exercise.

Table 2 Attribute levels of the SP experiment

Current option attribute minus off-peak option attribute	Attribute levels		
	Level 0	Level 1	Level 2
Travel cost (Ch$)	10	30	50
Waiting Time (min)	0	-1.0* / -1.5**	-
Comfort	small difference	large difference	-

* Associated with Line 1
** Associated with Line 2

To define the hypothetical situations in the SP questionnaire a fractional factorial design of eight options was used (Kocur *et al*, 1982). Therefore, every respondent was faced with eight hypothetical pairwise comparisons. In addition to that, we had data available from the segmentation survey regarding time of travel, origin and destination station, trip frequency and purpose, access mode, and general information about the traveller such as sex, age, employment, working hours, number of people in the household, net monthly income and family income. Table 3 presents the characteristics of each card used in the SP survey form.

Table 3 Stated preference cards

Card	Current Travel Cost (Ch$)	New Travel Cost (Ch$)	Current Waiting Time (min)	New Waiting Time (min)	Current Comfort Level	New Comfort Level
1	120	90	2	2	bad	normal
2	120	110	2	3.0 / 3.5*	bad	good
3	130	80	2	3.0 / 3.5*	bad	normal
4	120	90	2	2	bad	good
5	120	110	2	2	bad	normal
6	120	90	2	3.0 / 3.5*	bad	normal
7	130	80	2	2	bad	good
8	120	90	2	3.0 / 3.5*	bad	good

* Values for Line 1 and Line 2 respectively.

Consistency analysis

It is very important to check the consistency of the answers given by the respondents in order to have data that will allow the estimation of good and representative models. We understand as an inconsistency when one or more answers do not follow the rational consumer assumptions implicit in the discrete choice model theory (Ortúzar and Willumsen, 1994).

However, to detect inconsistencies is not a simple matter; it requires to construct a set of selection rules consistent with rational behaviour. Unfortunately, the analyst is capable of detecting only some of them, as the others depend on the respondent preferences.

The rules are constructed after a detailed analysis of all the attribute values in each alternative offered in the exercise. In this case we were able to determine the rules that are shown in Table 4. As can be seen, in card number seven for example not only the travel cost is cheaper in the off-peak option, but it has also a smaller waiting time and a better comfort level. Therefore if the respondent does not choose it in this card, she should not choose the off-peak option in any other card, as in all others this alternative has at least one worse aspect. On the other hand, if the respondent chooses the off-peak option in the first card, she should also choose it in the fourth and seventh cards, because in both of them the option is even better than in the first card in at least one attribute.

After checking the data to find out the answers that caused inconsistencies, we proceeded as follows: the wrong answers were eliminated if they were two or less (recall that there were eight answers per questionnaire); otherwise, the complete set of responses for that individual was dropped.

Another important aspect to consider was the search for biased answers. Belonging to this group were those respondents travelling in the peak period only five minutes or less from the off-peak period who declared never to change their time of travel. Before eliminating these respondents we checked that they did not belong to a particular socio-economic group.

Table 4 Rules to detect inconsistencies

If he/she chooses	in card No.	should choose	in card(s)..
Off-peak option	1	Off-peak option	4 and 7
Off-peak option	2	Off-peak option	4, 7 and 8
Off-peak option	3	Off-peak option	7
Off-peak option	4	Off-peak option	7
Off-peak option	5	Off-peak option	1, 4 and 7
Off-peak option	6	Off-peak option	1, 3, 4, 7 and 8
Off-peak option	8	Off-peak option	4 and 7
Current option	1	Current option	5 and 6
Current option	3	Current option	6
Current option	4	Current option	1, 2, 5, 6 and 8
Current option	7	Current option	All
Current option	8	Current option	2 and 6

Characteristics of the sample

Before analyzing the sample there are a few things to mention. Firstly, in this work we used only the data considering trips to work or study of people who paid the normal Metro fare (ie. we excluded from the analysis those respondents who paid student fares).

Secondly, to analyze the behaviour of travellers in the context of this work we looked first at their working hours and time restrictions. The annual survey collected by Metro (Metro, 1993) revealed that about 70% of the morning peak travellers were employers or dependent professionals, and this figure dropped to 57% in the evening peak. Then, when analyzing the working hours of the sample, we identified two different groups. The first is composed of travellers who have a set working time and fixed entrance and exit working hours. This is very important, because if one of these people started working before his entrance time, in general he would not be able to go out before his set exit time. The second group is formed by travellers who are able to delay their entrance time or to move forward their exit time. However, we expect that if these people changed their time of travel, they would not change their total working hours. Based on these assumptions and in the expenditure rate model of Jara-Díaz and Farah (1987), Bianchi (1995) demonstrated that two travellers belonging to each of the above groups associate a different marginal value to one extra minute in the time displacement required to travel outside the peak period by comparing its first and second derivates. For this reason we proceeded to aggregate the answers of people who were either faced with the possibility of travelling before their current time if travelling in the morning peak, or after their current time if using the Metro in the evening peak ("extreme" samples). We also grouped together the information coming from people who were faced with the alternative of travelling after their current time if they were travelling in the morning peak or before their current time if using the Metro in the evening peak ("medium" samples). This data aggregation procedure brought important improvements in terms of model estimation.

The data was aggregated into four samples: Line 1 Extreme and Medium, and Line 2 Extreme and Medium. In general (as shown in Tables 5 and 6) there is not much difference between the characteristics of the samples, although the travellers of Line 2 declared to have smaller income than the travellers of Line 1. If we look at trip frequencies, we can see that 83.7% of the respondents make the same trip every day. Also, the more common access modes were bus and by foot and it is interesting to note that the people between 19 and 50 years of age did respond very similarly, a result which might be expected given that they are of working age. We also analyzed the answers of people belonging to the same income group, where these groups were defined as follows:

Low Income : Net family income < Ch$ 150,000

Medium Income : Ch$ 150,000 < Net family income < Ch$ 450,000

High Income : Net family income > Ch$ 450,000

Table 5 Statistical distribution of the variables for travellers of Line 1

SAMPLE		L 1 Extreme		L 1 Medium	
		Number	%	Number	%
TOTAL		211	100	78	100
Type	before peak period	125	58.96	31	39.74
	after peak period	87	41.04	47	60.26
Access mode	on foot	95	44.81	41	52.56
	bus	70	33.02	19	24.36
	car	21	9.91	10	12.82
	shared taxi	22	10.38	7	8.97
	other	4	1.89	1	1.28
Sex	male	117	55.19	46	58.97
	female	95	44.81	32	41.03
Frequency	daily	173	81.60	63	80.77
	2-3 / week	22	10.38	11	14.10
	1/ week	11	5.19	2	2.56
	less than 1/ week	6	2.83	2	2.56
Purpose	commute	183	86.32	63	80.77
	work	7	3.30	5	6.41
	study	22	10.38	10	12.82
Age	18 or less	2	0.94	2	2.56
	19—30	99	46.70	34	43.59
	31—50	95	44.81	34	43.59
	more than 50	16	7.55	8	10.26
Occupation	work	192	90.57	68	87.18
	study	20	9.43	10	12.82
Working time	average (hrs/day)	8.5		8.5	
Nº of residents	average	4.1		4.0	
Net monthly income of the respondent (thousands Ch$)	less than 80	23	10.85	10	12.82
	80-150	67	31.60	16	20.51
	150-300	42	19.81	24	30.77
	300-450	34	16.04	6	7.69
	450-600	11	5.19	6	7.69
	600-800	9	4.25	3	3.85
	800-1000	7	3.30	3	3.85
	more than 1000	2	0.94	3	3.85
	no response	17	8.02	7	8.97
Net family income of the respondent (thousands Ch$)	less than 80	5	2.36	3	3.85
	80-150	32	15.09	12	15.38
	150-300	55	25.94	19	24.36
	300-450	42	19.81	15	19.23
	450-600	28	13.21	9	11.54
	600-800	21	9.91	3	3.85
	800-1000	8	3.77	8	10.26
	more than 1000	18	8.49	9	11.54
	no response	3	1.42	0	0.00

Table 6 Statistical distribution of the variables for travellers of Line 2

SAMPLE		L 2 Extreme No.	%	L 2 Medium No.	%
TOTAL		131	100	39	100
Type	before peak period	78	59.54	19	48.72
	after peak period	53	40.46	20	51.28
Access mode	on foot	66	50.38	21	53.85
	bus	36	27.48	9	23.08
	car	9	6.87	1	2.56
	shared taxi	19	14.50	8	20.51
	other	1	0.76	0	0.00
Sex	male	73	55.73	25	64.10
	female	58	44.27	14	35.90
Frequency	daily	117	89.31	31	79.49
	2-3 / week	6	4.58	5	12.82
	1/ week	6	4.58	2	5.13
	less than 1/ week	2	1.53	1	2.56
Purpose	commute	111	84.73	28	71.79
	work	9	6.87	6	15.38
	study	11	8.40	5	12.82
Age	18 or less	2	1.53	1	2.56
	19—30	65	49.62	21	53.85
	31—50	58	44.27	12	30.77
	more than 50	6	4.58	5	12.82
Occupation	work	121	92.37	35	89.74
	study	10	7.63	4	10.26
Working time	average (hrs/day)	8.0		8.3	
Nº of residents	average	4.1		4.3	
Net monthly income of the respondent (thousands Ch$)	less than 80	19	14.50	6	15.38
	80-150	44	33.59	10	25.64
	150-300	39	29.77	14	35.90
	300-450	13	9.92	5	12.82
	450-600	2	1.53	0	0.00
	600-800	2	1.53	1	2.56
	800-1000	2	1.53	0	0.00
	more than 1000	0	0.00	0	0.00
	no response	10	7.63	3	7.69
Net family income of the respondent (thousands Ch$)	less than 80	4	3.05	2	5.13
	80-150	21	16.03	7	17.95
	150-300	46	35.11	13	33.33
	300-450	32	24.43	10	25.64
	450-600	16	12.21	1	2.56
	600-800	6	4.58	4	10.26
	800-1000	4	3.05	2	5.13
	more than 1000	2	1.53	0	0.00
	no response	0	0.00	0	0.00

We noticed that as income increased the proportion changing time of travel decreased. Finally we analyzed how people behaved as the amount of time they had to change their current time of travel increased; for this we stratified the sample by 15 min intervals and noticed that as the time they had to change increased, their preference for changing their current travel time decreased. However, if we stratify the sample into groups of different time interval sizes these results vary (we will comment on this later).

MODEL ESTIMATION

Description of the variables used

Using the information collected in the segmentation survey and the attributes and variation levels of the SP survey, we defined the following variables for the calibration stage; notice that whenever a variable is measuring a difference, it means its value in the current option less its value in the off-peak option:

- *Faredif* Fare difference between alternatives (Ch$).
- *Wtime* Headway difference between alternatives (min); associated to waiting time.
- *Standing* Comfort level 1; takes the value of one when a change between travelling standing very crowded and standing less crowded is considered, and zero otherwise. This value is multiplied by the number of Metro stations the person passes by between her origin and destination.
- *Seated* Comfort level 2; takes the value one when a change between travelling standing very crowded and travelling seated is considered, and zero otherwise. This value is also multiplied by the number of Metro stations the person passes by between the origin and destination of her trip.
- *Tdis* Time displacement required to travel outside the peak period. We assumed that this variable would have a non linear behaviour, so we divided it into different segments.
- *Sex* Dummy which takes the value of one for females and zero for males.
- *Age* Dummy which takes the value of one for people between 19 and 50 years old and zero otherwise.
- *Freq* Frequency of the trip that the respondent was making at the time of the survey. Takes the value of one if it is a daily trip and zero otherwise.
- *Before* Dummy which takes the value of one if the respondent answered the form for travelling before the current time and zero otherwise.

The estimated parameters for these attributes should have the following signs:

- *Faredif, Wtime, Standing and Seated* : Negative sign; in the case of the first and the last two, the reason is obvious (an increase in the corresponding variable diminishes the utility of the current option). In the case of *Wtime* the reason is more complex; as the train frequency is always better or at least equal in the current option, the value of this variable is always negative, and for this reason its parameter should also be negative (as the difference increases, the attractiveness of the off-peak option decreases).
- *Tdis* : Positive sign; the bigger the amount of time the traveller needs to adjust the timing of his/her trip, the more attractive the current option is.

The parameters of the other variables do not have *a-priori* determined signs under the theory used in this estimation process.

Model estimation

An important element that deserves some space here is the modelling approach developed to estimate a good parameter for the *Tdis* variable. We expected a non linear behaviour for this variable (as reported in Bates *et al*, 1989; Johnston *et al*, 1989; Hendrickson and Plank, 1984 and Polak *et al*, 1993). For this reason we tried different ways to model this effect but did not obtain satisfactory results; we believe this is a problem of the data caused partially by the following problem. The people interviewed in the survey (segmentation questionnaire) were asked to fill the SP exercise later at home or at their offices. Therefore it is possible that they were not able to recall their time of travelling accurately, so they just answered in accordance to what they could calculate or remember later (the SP design did not incorporate the time of travel and the time displacement required to travel in the off-peak period).

We believe this to be the main reason why everytime we tried to model the *Tdis* variable more finely (ie. taking into account marginal value differences and trying to estimate quadratic and spline functions) we failed to obtain reasonable estimators. To solve this problem we were forced to estimate three dummy variables, each of them representing one segment of the whole range of time displacements considered in the analysis. The time intervals selected were those that produced the best goodness of fit. Finally, and in order to add more realism to the travel time adjustments considered we decided to use only time displacements not bigger than 45 minutes.

In the previous section we mentioned that we observed some income effect in the respondents' preferences. Because of this we calibrated different parameters for the fare difference depending on the income segment of the respondent. Another aspect worth mentioning, is that in each sample we tried to model the people considering to travel before their current time separately from the people considering to travel after it; however most parameters did not show significant differences at the 95% level.

In order to analyze our rating data we require as usual to find a quantitative relationship between the set of attributes and the responses expressed in the semantic scale. For this we need to associate a numerical value R_m to each row m (m = 1, ..., M) of the experiment and postulate a linear model such as:

$$\theta_0 + \theta_1 X_1 + \theta_2 X_2 + \ldots + \theta_k X_k = r_j$$

where θ_0 is a constant, X_k is the difference between the kth attributes of the two competing time of travel alternatives; θ_k is the coefficient of X_k and r_j represents a transformation of the response of individual j; (ie. it defines a unique correspondence between the semantic scale and the numerical scale R_m). Thus, when the questionnaire is completed we obtain the chosen values of the dependent variable R_m and knowing the attribute values X_k we can perform, for example, a *multiple regression analysis* to estimate the values of θ_k.

However as there are innumerable numerical scales that could be associated to the response scale it may probably occur that the results of the analysis (estimated coefficients, their ratios and model goodness of fit) depend on the definition of R_m; this hints at the importance of choosing the scale correctly. Due to this, four different methods were used at the model estimation stage:

i) Linear Regression (LR) after applying the Berkson-Theil transformation to the standard choice probabilities (0.1; 0.3; 0.5; 0.7 and 0.9) associated to the semantic scale. These were selected because of their use in many SP ratings studies in the transport field (see for example, Bates and Roberts, 1983; Fowkes and Tweddle, 1988; Ortúzar and Garrido, 1994b).

ii) LR model where the response scale is determined during the process of maximizing the model goodness of fit, effectively considering each value of the scale (R_1, R_2,..., R_5) as an additional variable (Ortúzar and Garrido, 1994a). To find the optimum we used a coordinate search method starting with the standard values described above. The procedure consists simply of changing in turn each point of the scale (say R_i) by a small amount and estimating a LR model with the new values. The search continues until the R^2 index is maximized and the value of R_i is fixed. The procedure is repeated for each point of the scale (save for R_3 which is always kept as 0.5) in an iterative routine until a best fit is found in each case (that with the highest R^2). This process is repeated again to check for differences. However, unlike Ortúzar and Garrido (1994a) we found that the process did not always converge and in some cases the final outcome depended heavily on the starting values.

iii) Binary logit model with the following transformation of the semantic scale: each answer to the left of *Indifferent* is considered as a choice of the current option; in turn, each answer to the right of this sentence corresponds to a choice of the off-peak option. The answers marked "indifferent" were eliminated.

iv) Ordinal probit model, which provides a way of avoiding the problem described above (considering the modelling paradigm developed by McKelvey and Zavoina, 1975) by not requiring the analyst to specify the numerical scale *a priori* in order to estimate the model.

After analyzing the results of the above methods (for further details see Bianchi, 1995) we concluded that the best models were obtained using the ordinal probit estimation. They are presented in Tables 7 and 8. As it can be seen, all parameters have the expected sign and most of them are different from zero at the 95% level. In the case of the Line 1 Extreme Sample it can also be seen that the fare parameters between income segments are different and have a correct order (ie. the fare discount for travelling in the off-peak period for the people with higher income is less attractive than for the people with smaller income).

Table 7 Ordinal probit models for the extreme examples

LINE 1	EXTREME
Constant	0.1255 (0.80)*
Tdis2 (16-25) min	0.4939 (5.66)
Tdis3 (26-45) min	0.6287 (8.46)
Age	-0.4858 (-4.57)
Sex	-0.1801 (-2.87)
Faredif 1 (low income)	-0.0257 (-6.77)
Faredif 2 (medium inc.)	-0.0189 (-7.32)
Faredif 3 (high income)	-0.0061 (-2.37)
Wtime	-0.3294 (-3.44)
Standing	-0.0133 (-1.90)*
Seated	-0.0204 (-2.86)
Freq	0.3247 (3.78)
Before	-0.3110 (-4.78)
R^2	0.2366
Sample size	1,631

LINE 2	EXTREME
Constant	-1.6841 (-6.00)
Tdis2 before (11-30) min	0.3665 (3.11)
Tdis3 before (31-45) min	1.0395 (8.82)
Tdis2 after (11-30) min	0.8825 (6.71)
Tdis after (31-45) min	1.0235 (6.76)
Age	0.9877 (4.52)
Sex	-0.2708 (-3.40)
Faredif1 (low income)	-0.0299 (-6.16)
Faredif 23 (m & h inc.)	-0.0128 (-4.56)
Wtime	-0.3172 (-3.42)
Comfort	-0.0008 (-0.13)*
Freq	0.3744 (2.87)
R^2	0.2795
Sample size	987

* Not statistically significant at the 95% level

In the model for the Line 2 Extreme Sample we had to calibrate different parameters for each time interval, depending on the class of displacement required to travel outside the peak period (before or after it). In this case, the medium and high income fare parameters did not show significant differences. On the other hand, the respondents in this sample did not reveal major preference differences between comfort levels, so we calibrated just one parameter labelled *Comfort*.

Finally, in the case of the Line 1 Medium and Line 2 Medium models, none of the parameters came out as different from its homologue at the 95% level, so we calibrated just one model with both samples. However all the small differences put together justified the estimation of a dummy variable called *Line*, defined as having the value of one if the traveller used Line 1 and zero otherwise.

Table 8 Ordinal probit model for the medium samples

LINE 1-2	MEDIUM
Constant	-0.2534 (-1.00)*
Tdis2 after (6-30) min	0.8538 (6.09)
Tdis3 after (31-45) min	0.2484 (1.68)*
Tdis2 before (6-30) min	2.4370 (13.13)
Tdis3 before (31-45) min	0.3893 (2.18)
Age	-0.3546 (-2.61)
Sex	-0.0971 (-1.07)*
Faredif 1 (low income)	-0.0380 (-7.43)
Faredif 23 (m & h inc.)	-0.0076 (-2.53)
Wtime	-0.4526 (-6.29)
Comfort	-0.0240 (-2.38)
Line	-0.3612 (-3.77)
Freq	0.3066 (2.75)
R^2	0.4508
Sample size	895

* Not statistically significant at the 95% level.

PREDICTIONS AND COMPARISON WITH REALITY

To calculate the choice probabilities of both alternatives we used the sample enumeration procedure. However, we could not use the estimated models directly for prediction because their constants make them reproduce the choices declared by the respondents in the SP exercise and this could have not much to do with the actual choices. To solve this problem we tried first to adjust the constants such that if we ran the models with no fare difference between the current and off-peak options, they would predict a small amount of change which could be interpreted as "natural peak spreading" (see Johnston *et al*, 1989). Unfortunately, this procedure makes the impact of the different fare discounts heavily dependent on the value chosen for the constant. For this reason we used an approximation of the pivot-point formulation (Ortúzar and Willumsen, 1994) which only takes into account the attributes that change between the base and design year situations. Unfortunately, the pivot-point approach requires knowledge of the base year market shares of each option and these are obviously unknown in our case. For this reason our approximation just consists of ignoring the estimated constants (as they would not vary between base and design year). We are aware that this approach needs some improvement and developments in this area are highly desirable.

We applied the models to the segmentation sample collected by DICTUC (1993) which did not show major distributional differences in comparison with the population (Metro, 1993). The predictions were made under the assumption that travellers did not change their travel times by more than 45 minutes (considering what was offered in this exercise).

Unfortunately, when the Santiago Metro implemented its new pricing strategy in February 1994 they defined the morning peak starting at 7:15 (instead of 7:30 as was considered in this study) and the segmentation sample had information from 7:30 onwards only. To solve this problem we decided to use data from the annual survey collected by Metro (Metro, 1993) for passengers between 7:15 and 7:29. As this survey does not have all the variables required we assumed they had the same statistical distribution as in the segmentation sample.

In the following tables (9 to 11) we present the predictions obtained when using the models with its original constant and with the pivot-point (no constant) formulation, and the results observed in practice when the new pricing strategy started to operate. In the last two tables the data corresponds to an average of what happened between March and September 1994 and the numbers given are expressed in real terms (ie. they are net from the normal demand increase observed in those months). We also present the variations actually observed in the half hour periods which are just before and after the peak period under consideration.

Table 9 Predictions obtained using the ordinal probit model

	LINE 1		LINE 2	
	Morning peak	**Evening peak**	**Morning peak**	**Evening peak**
Original constant	- 8.63 %	- 6.44 %	- 6.83 %	- 4.41 %
Pivot-point	- 8.48 %	- 6.69 %	- 3.89 %	- 3.06 %

Table 10 Observed impacts for Line 1

Morning	**6:45—7:15**			**7:15—9:00**			**9:00—9:30**		
	93	**94**	**%**	**93**	**94**	**%**	**93**	**94**	**%**
Average	4009	4119	1.13	56887	55020	-5.03	12402	13361	6.01

Evening	**17:30—18:00**			**18:00—19:30**			**19:30—20:00**		
	93	**94**	**%**	**93**	**94**	**%**	**93**	**94**	**%**
Average	16669	16646	-1.74	71111	67860	-6.29	15114	15843	3.09

Table 11 Observed impacts for Line 2

Morning	**6:45—7:15**			**7:15—9:00**			**9:00—9:30**		
	93	**94**	**%**	**93**	**94**	**%**	**93**	**94**	**%**
Average	2320	2371	3.62	27757	26382	-3.72	4503	4696	5.60

Evening	**17:30—18:00**			**18:00—19:30**			**19:30—20:00**		
	93	**94**	**%**	**93**	**94**	**%**	**93**	**94**	**%**
Average	3686	3706	1.91	16254	15570	-2.95	4033	3958	-0.54

If we compare the predictions with what was observed in reality, we can say in general that they are indeed reasonable. For example, not only the range of values is reasonably close but the models predict more change in Line 1 than in Line 2 as was observed in practice. However in the case of Line 1 morning peak there are differences somewhat higher which may be due to the problems with the peak period duration described above. It can also be seen that the predictions obtained using the pivot-point approximation appear to be in closer agreement with the observed data than those obtained using the original constant.

Finally, there are some limitations that we should mention at this stage. Firstly, our models can only predict changes for people that need to adjust their time of travel in as far as 45 minutes; therefore any major adjustments that may have happened in reality (ie. changes of more than 45 minutes) were not predicted. On the other hand, we did not predict changes for travellers that were making a trip with a different purpose than going to or from work or study. Finally and perhaps more importantly, our SP exercise confronted people with a time of travel change given a fare reduction for travelling in the off-peak (we did this in order to avoid the complicated problem of some people facing a modal change otherwise), whilst the real policy implemented by the Metro company consisted precisely in a fare increase for those travelling in the peak.

CONCLUSIONS

The methodology developed in this work enable us to test, in general terms, the impacts of different Metro demand management strategies as it has been observed empirically that Metro travellers do adjust their time of travel when a fare discount and an improvement in comfort is offered.

About the method itself we can say first that the data aggregation approach used, which is based on a solid microeconomic basis, was supported empirically by our model estimation results. Another point worth mentioning is that we detected some income effect in the traveller preferences that was confirmed with the estimation of different fare parameters for the various income groups. We also explored different ways to model the non-linear effect of the time displacement variable. Although we observed a non-linear behaviour in the respondent answers, we could not model this with great precision as inconsistencies were found in the data. We believe that this problem could be reduced if the SP survey included the time of travel and the time displacement required by travellers to change their trips to the off-peak period.

We tested four modelling approaches following the work of Ortúzar y Garrido (1994a) and we also found ordinal probit to provide the best modelling results,; however, unlike these authors we detected convergence problems in their optimal linear regression approach.

The simulation of the current Metro pricing strategy with our best models brought about good results when compared with data observed in practice. However we detected some problems when forecasting using the estimated model constants, because their aim is to reproduce the market shares of the estimation samples and this may obviously have not much to do with the actual shares. To solve this problem we used a naive approximation of the pivot-point formulation but future developments in this area are desirable.

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