A JOINT MODE/TIME-OF-DAY CHOICE MODEL USING COMBINED REVEALED PREFERENCE AND STATED CHOICE DATA

Pedro Lizana, Departamento de Ingeniería de Transporte y Logística, Pontificia Universidad Católica de Chile,Vicuña Mackenna 4860, Santiago, Chile.

Julian Arellana, Departamento de Ingeniería Civil y Ambiental, Universidad del Norte,Km. 5 Antigua vía a Puerto Colombia, Barranquilla, Colombia.

Juan de Dios Ortuzar, Departamento de Ingeniería de Transporte y Logística, Pontificia Universidad Católica de Chile,Vicuña Mackenna 4860, Santiago, Chile.

Luis Rizzi, Departamento de Ingeniería de Transporte y Logística, Pontificia Universidad Católica de Chile,Vicuña Mackenna 4860, Santiago, Chile.

ABSTRACT

The factors influencing trip departure time are taking more importance in practice since urban congestion is increasingly being addressed by travel demand management (TDM) strategies. In this paper we formulate and estimate a joint travel mode-departure time model for commuting trips using combining revealed preference (RP) and stated choice (SC) data. The information was gathered through a RP/SC/attitudinal survey applied to nearly 500 people that travel to work in the Santiago Metropolitan Area.
Travel time, cost and cost divided by the wage rate coefficients were fairly similar in both the RP and SC environments, while schedule delay penalties associated with early or late arrival to work differed between each type of data. The goodness of fit of the models decreased when higher time resolutions (i.e. length of departure time intervals) are considered.
From a simple exercise of forecasting the impacts of a hypothetic congestion charging scheme, it was found that the schedule delay coefficients derived from the SC context produce a smoother and less-peaked temporal distribution of travel demand than the RP parameters, and some implications regarding policy design were obtained as well. To achieve significant changes in traveller's time of day and mode choices, authorities should firstly incentivize companies to install policies allowing workers to have more flexible work arrival and departure times, and should also invest on improving the transit system with the revenues derived from the congestion charging scheme.

Keywords: time-of-day models, joint trip departure mode choice models, discrete choice models, mixed RP/SP modelling.

INTRODUCTION

The high congestion levels experienced by large urban areas require a comprehensive understanding of travel behaviour. Mode, departure time, and route choices are key decision processes that need to be fully understand in order to examine the temporal and spatial dimensions of travel demand. Car users can change their departure times to the shoulders of the peak period or to off-peak periods in an effort to reduce travel times. The factors influencing time-of-day (TOD) and mode choices are also taking increasing importance since the growing congestion in urban areas is increasingly being addressed by travel demand management (TDM) strategies, such as a congestion charging policy.

In the last decade, most models for the joint decision of trip departure time and mode choice using the seminal Scheduling Model (SM) proposed by Small (1982) have relied only on stated preference (SP) data (de Jong et al., 2003; RAND Europe, 2004; Hess et al., 2007; Arellana et al., 2012a). The process of collecting such data is generally less demanding on resources than collecting revealed preference (RP) data. Another advantage of choice models based on SP data is that the impact of TDM strategies not yet implemented can be tested. However, SP data can be less trustworthy than RP data when using models for forecasting purposes (Börjesson, 2008) because individuals may not choose their SP choice when faced with same option in reality. The last years have witnessed an increase in the number of practical time-of-day models estimated using large scale RP mobility surveys (Abou-Zeid et al., 2006; Popuri et al., 2008) and level-of-service data generated from a classical four step transport model to estimate the temporal distribution of velocities in the network. These models, however, only consider a time-of-day dimension.

The drawbacks of each data type can be addressed partially by combining them. We are aware of only two studies which have used mixed RP/SP data in a trip timing context: Börjesson (2008) and Tseng et al. (2011). However, while the former only considers mode choice in the SP component, the latter does not even consider a mode choice dimension.

The purpose of this paper is to present the estimation of a joint travel mode-departure time model for trips to work using combined RP/SP data, as well as to assess the potential policy implications that arise from our model results. Both dimensions, mode and trip timing choices, are considered in both the RP and SP datasets.

The remainder of the paper is organized as follows. First, a brief theoretical background of trip departure time models is given. This is followed by a description of our RP and SP datasets. The model estimation results and a brief forecasting example are then presented. Finally, the implications of our results for policy design and further research are given.

THEORETICAL BACKGROUND

The most common approach for modelling time-of-day choice is the scheduling model (SM) proposed by Small (1982) and motivated by the earlier work of Vickrey (1969). The SM, described by equations (1) to (5), discretizes time into several departure time intervals which individuals choose from. The basic trade-off of the SM relates to travelling at less congested hours but arriving earlier or later, to work, from a certain preferred arrival time (PAT).

$$V_i = \beta_{TT}\, TT_i + \beta_{SDE}\, SDE_i + \beta_{SDL}\, SDL_i + \delta_L\, d_L \tag{1}$$

where:

$$SDE_i = Max\{-SD_i, 0\} \tag{2}$$

$$SDL_i = Max\{0, SD_i\} \tag{3}$$

$$d_L = \begin{cases} 1 & if\ SDL_i > 0 \\ 0 & if\ SDL_i = 0 \end{cases} \tag{4}$$

$$SD_i = (Arrival\ time_i - Preferred\ arrival\ time) \tag{5}$$

With this notation, the subscript i refers to alternatives (given by discrete time periods), TT_i indicates the travel time when departing at period i, SD_i denotes schedule delay, and SDE_i and SDL_i represent SD for arriving early or late, respectively. These three time components have associated marginal utility coefficients that need to be estimated (defined as β_{TT}, β_{SDE}, and β_{SDL}); d_L is an additional parameter which represents a penalty for arriving late at the destination (independent of the actual amount of 'lateness').

The discrete approach to model time-of-day preferences allows using discrete choice models. These models have been extensively researched (Ortúzar and Willumsen, 2011) and are both relatively simple to estimate and to incorporate into a four-step transport planning model. Nevertheless, the discrete framework has some shortcomings that arise from the need to discretize time, a variable that is essentially continuous. Firstly, it is likely that the random errors of the trip departure time alternatives are correlated (de Jong et al., 2003), especially for nearby time intervals and when use is made of time periods with a higher temporal resolution (e.g. 15 min). This issue, however, can be addressed by using model structures such as the Hierarchical Logit (HL) model (Williams, 1977), Ordered Generalized Extreme Value (OGEV) model (Small, 1987; Bhat, 1998a), or the highly flexible Mixed Logit (ML) model, which can approximate any discrete choice model based on random utility theory (McFadden and Train, 2000).

Another issue, which cannot be mitigated even by the ML model structure, is that the length of the time intervals is generally determined arbitrarily by the modeller (Habib, 2012), and models with different time intervals will likely lead to different results (Bhat and Steed, 2002). In the literature, the length of the time-of-day alternatives vary from 5 min (Small, 1982) to fairly aggregate time periods (Steed and Bhat, 2000; Tringides et al., 2004). Only one study (Hess et al., 2007) compares models estimated using intervals of different length; it was found that models with 1-hour time periods outperformed in most cases models with 15 min intervals and also with coarser (peak, off-peak and inter-peak) time periods. More research is needed regarding this issue, so that modellers may have more tools to choose a specific time period length.

The choice of when to travel has been studied jointly with other decisions, such as choosing work duration (Habib, 2012), the daily scheduling of activities (Wang, 1996; Ettema et al., 2004; 2007), route (Mannering, 1989; Khattak et al., 1995) and mode (Hendrickson and Plank, 1984; Bhat, 1998a; 1998b; de Jong et al., 2003; Hess et al., 2007). Despite the fact that the joint mode-TOD choice has received the most attention in the literature, when modelling both decisions it is still an important result to assess if individuals are more susceptible to vary their transportation mode or their times of travel in response to changes in level-of-service variables, such as when a TDM policy is implemented.

Existing joint mode-TOD discrete choice models have few joint alternatives. It is common that the models estimated with SP data consider only four alternatives (one for mode change and three for departing earlier than, later than and at a time similar to the observed departure time). In models estimated with RP data the maximum number of mode-TOD alternatives reported was 28 (four modes and seven TOD alternatives in Hendrickson and Plank, 1984), followed by 15 (three modes and five periods in Bhat, 1998a; 1998b). As the number of joint alternatives rises exponentially when a new mode or period is incorporated, limited data availability has apparently precluded from modelling the problem at a more disaggregated level.

DATA

REVEALED PREFERENCE

The RP databank was constructed from a trip departure time survey of nearly 500 individuals in Santiago, Chile (Arellana et al., 2013). The survey collected trip diary information for a specific day in 2011, as well as socio-demographic data and employment characteristics. Respondents were requested also to participate in two customized stated choice (SC) games purposely designed by pivoting on the RP data for each individual.

The RP databank considers nine modes. The number of time periods varies because one of the purposes of our research was to evaluate the effect of using different time period lengths; the lengths proposed were 15, 30 and 60 min (hereafter referred as 15min, 30min and 1-hour databanks). The available modes are: (i) car-driver, (ii) car-passenger, (iii) taxi, (iv) walk, (v) bus, (vi) metro, (vii) bus-metro, (viii) shared-taxi and (ix) a composite mode, called combination-metro[1] , that groups together trips by four modes that transfer to/from metro (taxi, shared-taxi, car-driver and car-passenger).

Table 1 shows the modal split and trip departure time distributions of the RP sample; as can be seen, car-driver, bus and metro are the dominant modes. The observed departure time for

[1] The grouping was made to reduce the number of joint mode-TOD alternatives and because the number of choices of the four individual combined modes was very low.

trips to work ranged from 5:00 to 14:00. It is worth noting that the alternatives 5:00-7:00, 9:00-11:00 and 11:00-14:00 are fixed and longer than the remaining ones because only a few people choose them. The numbers of trip departure alternatives for the 15min, 30 min and 1-hour databanks are 11, 7 and 5, respectively. This traduces into 99 (9 times 11), 63 (9 times 7) and 45 (9 times 5) joint mode-TOD alternatives (Lizana, 2013).

Table 1 - Observed modal split and trip departure time distributions

Modal split (%) Distribution		15 min (%) distribution		30 min (%) distribution		1-hour (%) distribution	
Car-driver	(21)	5:00-7:00	(6)	5:00-7:00	(6)	5-7	(6)
Car-passenger	(8)	7:00-7:15	(6)	7:00-7:30	(13)	7-8	(46)
Taxi	(3)	7:15-7:30	(7)	7:30-8:00	(32)	8-9	(45)
Walk	(6)	7:30-7:45	(16)	8:00-8:30	(33)	9-11	(3)
Bus	(22)	7:45-8:00	(17)	8:30-9:00	(12)	11-14	(1)
Metro	(18)	8:00-8:15	(20)	9:00-11:0	(3)	**Total**	**100**
Bus-metro	(13)	8:15-8:30	(13)	11:0-14:0	(1)		
Shared-taxi	(3)	8:30-8:45	(8)	**Total**	**100**		
Combination-metro	(6)	8:45-9:00	(4)				
Total	**100**	9:00-11:00	(3)				
		11:00-14:00	(1)				
		Total	**100**				

The survey collected data regarding the route choices made by every respondent for their chosen mode. The alternative modes were determined using a variety of programs. The car (driver and passenger), taxi, shared-taxi and combinations of these four options with the metro system, were generated with TransCad (www.caliper.com/tcovu.htm) using as criteria the route with smaller travel time. The mass transit options (bus, metro and combination of bus and metro) were created using a web application provided by Transantiago, the integrated public transport system of the city[2], which delivers the fastest route for any origin-destination pair. Finally, the walking alternatives were created using GoogleMaps.

The trip departure time alternatives were determined using as a reference point the chosen (or observed) departure time; 15 min (or 30 min/one hour for the other two databanks) were added and subtracted to the observed departure time until the entire spectrum of TOD alternatives was covered. As an example, Table 2 illustrates the trip starting time of the TOD alternatives for an individual who declared having departed to work at 8:50.

The level-of-service (LOS) data were gathered with an uncommon level of precision. For the private road network, vehicles instrumented with GPS devices circulated Santiago during the week that the RP component of the survey was carried out. The city was divided into the 750 zones available for the strategic transport model of Santiago (ESTRAUS[3]) and the GPS

[2] www.transantiago.cl
[3] http://www.sectra.gob.cl/metodologias_y_herramientas_de_transporte/metodologia/estraus_02.html

information was assigned to each zone using GIS software. The speed for a specific zone and time interval was calculated as the average speed reported by all the GPS instrumented-vehicles that circulated in that particular zone and time interval. Therefore, for each zone a temporal distribution of speeds was obtained, and that distribution was assigned to all the links inside the zone.

Table 2 - Example of alternative trip starting times for observed departure time at 8:50

15 min		30 min		1-hour	
5:00-7:00	6:50	5:00-7:00	6:50	5:00-7:00	6:50
7:00-7:15	7:05	7:00-7:30	7:20	7:00-8:00	7:50
7:15-7:30	7:20	7:30-8:00	7:50	**8:00-9:00**	**8:50**
7:30-7:45	7:35	8:00-8:30	8:20	9:00-11:00	9:50
7:45-8:00	7:50	**8:30-9:00**	**8:50**	11:00-14:00	11:50
8:00-8:15	8:05	9:00-11:0	9:20		
8:15-8:30	8:20	11:00-14:00	11:20		
8:30-8:45	8:35				
8:45-9:00	**8:50**				
9:00-11:00	9:05				
11:00-14:00	11:05				

For the metro network, the underground company provided information about travel times between each pair of consecutive stations plus the waiting time at each station; both variables had a 15 min resolution. For the bus system, Transantiago gave us GPS data (bus location and speed every 30 seconds) for all services operating in the city during the survey week. This huge amount of data was processed using the methodology devised by Arellana et al. (2012b); this gives as outputs the travel time between consecutive bus stops and the waiting time at each stop for any temporal resolution desired (in our case 15, 30 and 60 min). The walking times (access and transfer) of the bus and metro modes were determined using GoogleMaps. Finally, it is worth mentioning that the resolution of the LOS data used in each databank was consistent with the interval length in each case (i.e. 15, 30 and 60 min). This was done with the aim of evaluating if LOS data aggregation had a negative impact on model results.

STATED CHOICE

Two SC experiments were presented to the majority of respondents of the RP component of our general survey. The experiments comprised an efficient design optimized in two steps considering the following issues: (i) the dependency between the levels of two attributes of a given alternative (for example, cost and trip starting time), (ii) the fact that the variables presented to respondents are not the same that are used in the model and (iii) a customized design based on the RP answers (for more details regarding the experimental design see Arellana et al., 2012a). The objective of these experiments was to evaluate the effect on trip timing and mode choice of two TDM policies not yet implemented in Santiago: (i) a congestion charging scheme and (ii) a flexible working schedule system.

The first experiment focused on morning commuting trips[4]. Every respondent had to answer five choice situations, where each situation comprised four alternatives with their respective attributes. Three of these alternatives consisted of travelling in the same mode, but at different times: (i) start trip at a time similar to that observed in the RP component, (ii) start trip earlier (iii) and start trip later than the observed starting time. The fourth alternative entailed the option of switching mode departing at a time closer to the observed. For those people who had used public transport in the RP component, the alternative mode was car in case it was available; otherwise the option was a shared-taxi. For those who chose private transport, the alternative mode was public transport.

The attributes of each alternative were travel time (similar to that reported by the respondent), trip starting time, arrival time at work, monetary cost (in Chilean currency), a larger travel time that was implied to occur once a week (i.e. a measure of travel time variability in the network) and comfort of the trip. The latter only appeared for the public transport alternatives and considered vehicle occupation and whether the trip was made standing or seated. Figure 1 illustrates an example of a choice situation for a public transport user.

Choice Situation: 2	Option A	Option B	Option C	Alternative mode
Departure time to work	7:06	8:21	9:20	8:25
Usual travel time to work (Usual arrival time to work)	50 (7:56)	59 (9:20)	45 (10:05)	40 (9:05)
Travel time to work once a week (Usual arrival time to work)	60 (8:06)	74 (9:35)	54 (10:14)	48 (9:13)
Comfort	Crowded vehicle, standing	Crowded vehicle, standing, usually have to wait next for boarding	Half crowded vehicle, standing	
Adittional cost ($)	$ 493	$ 527	$ 476	$ 1,500
¿Which option would you choose?	▪	▪	▪	▪

23% Previous Next

Figure 1 - Example of choice scenario for a public transport user

ESTIMATION RESULTS

Several types of models were estimated using Biogeme (Bierlaire, 2003). Table 3 summarizes our main results (parameter values with their robust t-tests) for the 15min databank. The first (15_MNL) is a multinomial logit (MNL) model (both in the RP and SC utility functions), whereas the second (15_ECL) has an error component logit (ECL) structure in the SC utilities (the RP utilities remain a MNL model). The latter flexible structure allows

[4] The second experiment focused on tours composed of the trips to and from work. As the models estimated in this paper are only for the morning trips to work, the second experiment was not used.

the model to treat correctly the SC data pseudo panel effect (multiple answers made by each respondent).

Table 3.RP/SC model estimation results for 15min databank

Model	15_MNL		15_ECL	
Coefficient	**Value**	**Robust t- test**	**Value**	**Robust t- test**
Level of service				
Travel time - RP/SC	-0.032	-4.0	-0.034	-3.5
Access (waiting+walking) time – RP	-0.071	-5.3	-0.071	-5.3
Transfer time public transport – RP	-0.1	-4.1	-0.1	-4.0
Transfer time metro-combination – RP	-0.63	-3.8	-0.64	-3.8
Cost - RP/SC	-0.00038	-3.3	-0.00038	-3.2
Comfort level: seated – SC	0.33	2.2	0.44	2.3
Travel time uncertainty – SC	-0.93	-1.2	-0.23	-0.3
Scheduling				
SDE – RP	-0.076	-11.0	-0.077	-11.0
SDE – SC	-0.022	-3.9	-0.028	-3.3
SDL – RP	-0.1	-11.0	-0.1	-10.0
SDL – SC	-0.021	-3.4	-0.029	-2.9
Dummy late to work - RP/SC	-0.32	-3.0	-0.37	-2.7
# intermediate stops to work – RP	3.5	3.2	3.5	3.2
Socioeconomic Interactions				
# licenses/# car relationship – RP	0.95	2.1	0.95	2.1
Cost/hourly wage rate (w) - RP/SC	-0.85	-3.6	-0.83	-3.3
SDE - High flexibility early – RP	0.04	4.4	0.04	4.4
SDE - Medium flexibility early – RP	0.025	3.3	0.025	3.3
SDL - High flexibility late – RP	0.042	2.8	0.041	2.7
SDL - Medium flexibility late – RP	0.02	1.7	0.02	1.7
Scale factor RP/SC				
σ_{RP} / σ_{SC} *	1.00	0.1	1.30	0.8
σ error component ** - RP	-	-	1.40	3.2
ASC – SC				
Departing early	-0.64	-3.0	-0.89	-2.5
Departing late	-0.85	-3.2	-1.1	-2.7
Switch mode	-1.4	-3.8	-1.8	-3.0
Log-likelihood	-2497.9		-2273.4	
$\bar{\rho}^2$	0.304		0.365	
No. of parameters	31		32	
No. of observations	1743		1743	

* t-test with respect to 1; ** 1000 draws were used.

The variables used in the models were divided into four groups: (i) level-of-service, (ii) scheduling, (iii) socioeconomic or interactions between socioeconomic variables and LOS or scheduling variables and (iv) mode specific constants (ASC). While the mode choice preferences are captured by the LOS variables, the TOD preferences are explained both by the LOS variables (mainly travel time) and the scheduling variables. The ASC allow the model to replicate the observed modal split, but are not shown in the table for limited space concerns (the interested reader may consult Lizana, 2013).

Regarding the LOS variables, the in-vehicle travel time and cost coefficients were the same in the RP and SC utilities. The transfer time, which was separated in two coefficients - one for the mass transit modes (combination of bus and metro) and another for the combination-metro mode - was only used in the RP utilities. Further LOS variables included only in the SC functions were a dummy for sitting comfort level (expected to have a positive effect), and a travel time uncertainty measure. The latter variable was defined as the percentage difference between the usual travel time and the once-a-week travel time shown in the experiment; it is expected to cause disutility because the bigger the percentage difference the more uncertain the travel times are.

The scheduling variables included in the model are the schedule delay early (SDE) and late (SDL) terms, and a dummy variable that takes the value of one if the individual arrived late to work (i.e. after the official work starting time) for that specific TOD alternative. It should be noted that this dummy is slightly different to the one proposed by Small (1982), shown in equation (4), because the lateness penalty here is defined with respect to the official work starting time and not with respect to the preferred arrival time (PAT). The schedule delay variables were different for the RP and SC utilities because when estimating the models separately the RP values were consistently higher than the SC values. Notwithstanding, the dummy late to work was considered generic across the RP and SC choices. Another scheduling variable considered here was the number of intermediate stops on the journey to work. The most common intermediate stops were dropping or picking someone on the way to work, and it was added only in the car-driver utility functions because driving should give more flexibility than other modes when making multiple stops on a journey.

Amongst the socioeconomic variables used was the ratio between the number of cars and the number of driving licenses in the household with a ceiling of one; therefore, the availability of cars in the household is limited by the number of licenses. This variable was added only in the car-driver and combination-metro modes, due to the fact that higher car availability should make these modes more attractive.

In addition to cost, a variable cost divided by the hourly wage rate (w) was also added to the utility function (and its parameter was the same for the RP and SC choices). Although at first sight it might appear theoretically and statistically mistaken to include it in the model, recently Jara-Diaz et al. (2012) have shown that in samples with relatively large coefficients of variation (CV) for income an inordinate increase in the values of time (VOT) tend to appear when using the traditional cost/w variable, misleading policy evaluations[5]. On the other hand, the VOT remains constant if only the cost parameter is used independent of the income CV. To solve this problem, the authors propose to use a model specification incorporating simultaneously both the cost and cost/w parameters.

[5] In our sample the income CV was 0.5, which implies that its standard deviation is half the value of the average income, and we found that the VOT increased by 50% when only the cost/w variable was used.

The degree of flexibility that workers have to adjust their arrival time to work (or work schedule flexibility) is an important variable when explaining time-of-day preferences. For example, individuals with a higher flexibility to arriving late to work could put less value on arriving late; therefore travelling later in the morning could be more attractive to them. In the survey, the work schedule flexibility was measured by the number of minutes respondents could arrive early or late with respect to their official work starting times. The work schedule flexibility was incorporated to the model by interacting the schedule delay terms of equations (2) and (3) with dummy variables for the degree of flexibility[6]. Three categories were defined for the degree of flexibility: less than 15 min early and late (low flexibility early and low flexibility late), up to 30 min (medium) and more than 30 min (high). The early flexibility dummies interact with the SDE term, while the late ones interact with the SDL variable. As can be seen, these interactions are statistically significant, suggesting that the level of work flexibility influences temporal choices.

To mix data from different sources a scale factor is needed (in this case multiplying the SC utilities) to equate the random error variances associated with each data type (Louviere et al., 2000). As can be seen in Table 4, the scale factor is statistically equal to one, which indicates that the variances of the RP and SC errors are equivalent. This is an interesting finding, since what is mostly found in joint RP/SC analysis is that the SC data has more variance than the RP data (Börjesson, 2008).

The variance of the error component (model 15_ECL) is statistically different from zero, revealing the presence of unobserved heterogeneity effects regarding the multiple SC responses by each individual. When compared to the appropriate MNL model, the error component model is clearly superior in terms of goodness of fit.

The model estimation results for the 30min and 60min databanks are only shown in Table 4. The 60min model (60_NL) follows a nested logit structure in which mode choice is located in the upper nest of the hierarchy and the TOD choice in the lower (i.e. the TOD alternatives have a higher degree of substitution than the mode alternatives). However, the only nests with structural parameter ϕ smaller than one (as required by the theory, Carrasco and Ortúzar, 2002) were for the modes car-passenger, car-driver, bus, bus-metro, walk and metro (see Table 5 for results). This implies that only for these modes the TOD alternatives would be correlated, while for the remaining modes the TOD alternatives would be independent.

Several NL structures (for example, first TOD choice followed by mode choice) were tested for the 15min and 30min databanks, but none of them was successful, leaving the MNL structure as the preferred one. This was an unexpected finding, since TOD alternatives with a higher time resolution (i.e. 15 min versus 30 min and 60 min) should be more correlated, as there are more time alternatives and they are more similar between them (the times of

[6] These interactions were only added to the RP utilities (they were also tried in the SC functions without success). It should be noted also that all individuals had all time periods available (the common practice in the literature).

departure are closer). A possible explanation for this could be that in the 15min and 30min databanks the correlation structure is actually more complex (recall that the number of mode-TOD alternatives are 99 and 63, respectively) than in the 60min base, and for this reason it cannot be handled by the NL model. One way to test this would be to use more flexible structures, for example, a cross-nested logit model or an error components logit model.

Table 4 - RP/SC model estimation results for 30min and 60min time databanks

Model	**30_MNL**		**60_NL**	
Coefficient	**Value**	**Robust t-test**	**Value**	**Robust t-test**
Level of service				
Travel time - RP/SC	-0.032	-4.1	-0.028	-4.3
Access (waiting+walking) time - RP	-0.056	-4.7	-0.042	-4.3
Transfer time public transport - RP	-0.074	-3.3	-0.054	-3.0
Transfer time metro-combination - RP	-0.55	-2.9	-0.36	-2.2
Cost - RP/SC	-0.00039	-3.3	-0.00035	-3.1
Comfort level: seated - SC	0.34	2.2	0.29	2.2
Travel time uncertainty - SC	-0.96	-1.2	-0.83	-1.2
Scheduling				
SDE - RP	-0.082	-11.0	-0.054	-7.2
SDE - SC	-0.023	-3.8	-0.02	-4.0
SDL -RP	-0.095	-11.0	-0.05	-7.0
SDL - SC	-0.022	-3.4	-0.019	-3.4
Dummy late to work - RP/SC	-0.37	-3.0	-0.3	-2.9
# intermediate stops to work - RP	3.4	3.0	3.2	2.9
Socioeconomic/Interactions				
# licenses/# car relationship - RP	0.94	2.1	1	2.4
Cost/hourly wage rate (w) - RP/SC	-0.85	-3.5	-0.77	-3.3
SDE - High flexibility early - RP	0.042	4.3	0.029	4.0
SDE - Medium flexibility early - RP	0.027	3.3	0.017	2.6
SDL - High flexibility late - RP	0.035	2.6	0.015	2.1
SDL - Medium flexibility late - RP	0.015	1.4	0.0043	0.7
Scale factor PR/PD				
$\sigma_{RP} / \sigma_{SC}$	1.00	0	1.10	0.5
ASC - SC				
Departing early	-0.67	-2.9	-0.58	-3.0
Departing late	-0.86	-3.2	-0.75	-3.3
Switch mode	-1.4	-3.7	-1.3	-3.8
Log-likelihood	-2217.5		-1968.5	
$\bar{\rho}^2$	0.343		0.385	
No. of parameters	31		37	
No. of observations	1743		1743	

Table 5 - Nested logit (NL) structural parameters for 60 min model

Nest	λ	Robust t-test*	$\phi=1/\lambda$
Car-passenger	1.7	1.78	0.58
Car-driver	1.6	2.01	0.62
Bus	2.6	2.6	0.39
Bus-metro	2.1	2.41	0.47
Walk	2.6	2.36	0.38
Metro	2.0	2.54	0.50

* t-test with respect to 1

Table 6 shows a comparative summary of the estimated models. There is an increase in $\bar{\rho}^2$ as the length of the time intervals increases (the 60min NL model is even superior to the 15min model with an error component in the SC utilities). Presumably this could be due to the fact that the more aggregate the TOD alternatives are, the easier it is for the model to replicate the observed temporal choices, hence increasing goodness of fit.

Table 6 - Comparative summary of estimated models

	15_MNL	15_ECL	30_MNL	60_NL
$\bar{\rho}^2$	**0.304**	**0.365**	**0.343**	**0.385**
Values of* (US$/hour)				
Travel time	6.3	6.9	6.3	5.9
Access time	14.0	14.4	10.9	8.9
Transfer time public transport	20.6	20.7	14.4	11.6
Transfer time metro-combination	125.0	128.4	106.9	77.3
RP trade-off ratios				
Low work flexibility:				
SDE/Travel time	2.4	2.2	2.6	1.9
SDL/Travel time	3.2	3.0	2.9	1.8
Medium work flexibility:				
SDE/Travel time	1.6	1.5	1.7	1.3
SDL/Travel time	2.6	2.4	2.5	1.6
High work flexibility:				
SDE/Travel time	1.1	1.1	1.3	0.9
SDL/Travel time	1.9	1.8	1.9	1.2
SC trade-off ratios				
SDE/Travel time	0.7	0.8	0.7	0.7
SDL/Travel time	0.7	0.8	0.7	0.7

*Using the exchange rate prevailing at the time of the survey 1 US$=500 Chilean $

The values of in-vehicle travel, access and transfer time progressively decrease when using more aggregate trip departure time alternatives. This change is more pronounced for access and transfer time, with reductions of up to 44% when comparing the 15min and 60min models. It is important to highlight that every minute of transfer time between a private mode (car, taxi and shared-taxi) and metro causes considerable more disutility than a minute of transfer time between mass transit modes. Also, access time has a higher value than travel time, but is less valued than transfer time. This means that although transfer and access time are technically the same (a sum of walking and waiting time), people tend to dislike more transferring as they have to change; this has been found also in recent independent work in the country (Navarrete and Ortúzar, 2012).

An important feature of the Scheduling Model is the trade-off ratios between the SDE and SDL parameters, and that of travel time. These give the relative values given to a minute of travel time compared to a minute early or late to work and are also shown in Table 5. In the RP dataset the SDE/Travel time and SDL/Travel time ratios are larger for people with low work schedule flexibility and smaller for individuals with high flexibility. This is reasonable, since individuals with higher work schedule flexibility surely put a lower value to being late or early to work. On the other hand, people with low flexibility levels must put a higher value to meeting their work schedule commitments. For these people, in some cases arriving late can even carry monetary penalties.

Also, in RP people tend to value more a minute early or late to work than one minute of travel time (in some cases up to three times more), while in SC case the contrary occurs (the SDE/Travel time and SDL/Travel time ratios are lower than one). These differences could be attributed to several reasons. In first place, it could be due to different temporal perspectives between the RP and SC choices (something similar was found by Börjesson, 2008). The RP choice is most likely a result of a long term adaptation process; therefore, changing permanently the trip departure time should implicate less time at home or less time available for other activities early in the morning or later in the afternoon. On the other hand, it is probable that in the SC experiment some people were willing to change sporadically their trip, but not permanently (given the trip conditions of the SC choice situation); therefore obtaining lower coefficients (in absolute value) for SDE (and SDL) in SC than in RP. A second explanation, which is complementary, is that the context of the SC experiment entailed the implementation of a flexible working schedule scheme in the respondents work (and the implementation of a congestion charge in the city as well). SC respondents were told that they could change their trip departure time ignoring their previously stated work schedule flexibility, with the condition that they had to work the same amount of hours in a week and consider their personal restrictions (e.g. activities with the family) as well. This is reaffirmed by the fact that the interactions between SDE (SDL) and the degree of work schedule flexibility were not significant in SC while in RP they were significant indeed. Also, the RP SDE(SDL)/Travel time ratios of the 60min model for people with high work flexibility levels are more similar to the same ratios in SC. This means that individuals with a high capacity to change their trips penalize a minute early or late to work in RP in very similar fashion to how all the SP respondents do.

FORECASTING EXAMPLE RESULTS

A setback of the Scheduling Model is that large-scale mobility surveys used to calibrate strategic transport models usually do not gather information about preferred arrival times (PAT) to work. Also, even if the PAT was available, predicting it with the same precision as in the databank used for estimation is not straightforward. Hence, it is common that when using

TOD models for practical purposes, the schedule delay (SD) variables are replaced by time-of-day alternative specific constants (ASC), leading to a loss in model fit (because the SD terms capture and explain the time-of-day travel preferences[7]). Therefore, it is interesting to compare the forecasting ability of TOD models with and without SD variables and also TOD models with different time resolutions.

A simple forecasting example, entailing a US$ 4 congestion charge to car drivers when arriving to work between 7:00 and 8:00 and a US$ 6 charge when arriving between 8:00 and 9:00[8], was conducted. When a combined RP/SC model is used in forecasting mode and the estimated model has different RP and SC parameters for certain potentially common variables, as in our case, the modeller faces a conflict that sometimes is not easy to resolve (see the discussion in Cherchi and Ortúzar, 2010). In particular, if it is believed that a specific parameter in the SC environment is more representative than that estimated for the RP environment the predictive utility function should include the SC coefficient multiplied by the RP/SC scale factor (which, in our case, was statistically equal to one). Since a TDM congestion charge policy does not operate in Santiago yet, the influence of this policy cannot be captured by RP parameters. The SC experiment, on the other hand, considered the implementation of a congestion charging scheme, thus we feel that the SC parameters should be more appropriate when evaluating this type of policy.

So, we decided to test the forecasting ability of three models per each time interval length (15, 30 and 60 min): (i) a model that uses the RP schedule delay coefficients (SD-RP), (ii) a model that uses the SC schedule delay coefficients (SD-SC) and (iii) a model that replaces the scheduling variables with time-of-day ASC. Due to the limited number of RP observations in the last specification, interactions between the ASC and socioeconomic characteristics (as suggested by Ben-Akiva and Abou-Zeid, 2012) were not considered.

Figures 2 through 4 show the trip departure time distributions after the application of the congestion pricing scheme proposed for the 15 min (15_MNL model), 30 min (30_MNL model) and one hour (60_NL) models, respectively. Each of these figures shows the temporal distribution for the ASC, SD-SC and SD-RP models after introducing the congestion charge. For comparison purposes the observed TOD choice distribution is presented too (the latter distribution does not consider the congestion charging scheme).

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[7] However, under certain circumstances, the time of travel preferences can be assumed constant for each market segment, therefore, they can be captured interacting the ASC with socio-economic information (Ben-Akiva and Abou Zeid, 2012).

[8] The exchange rate used was again 1 US$=500 Chilean $. Most survey respondents work at the city centre, an area that has been under study in recent years to apply a congestion charging scheme (Salata *et al*., 2013).

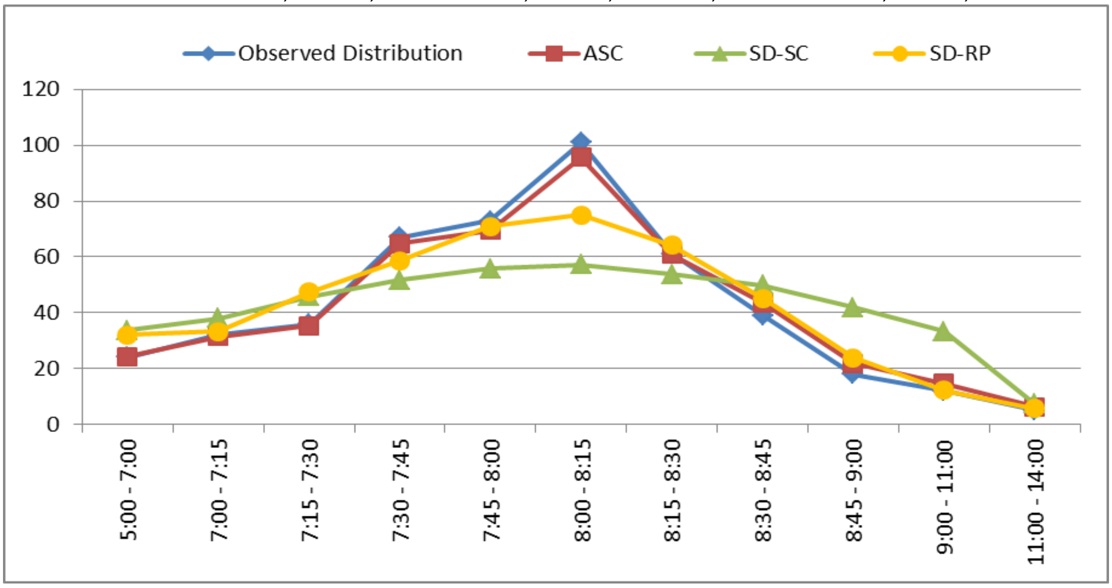

Figure 2 - Travel demand temporal distribution after congestion charging scheme: 15min

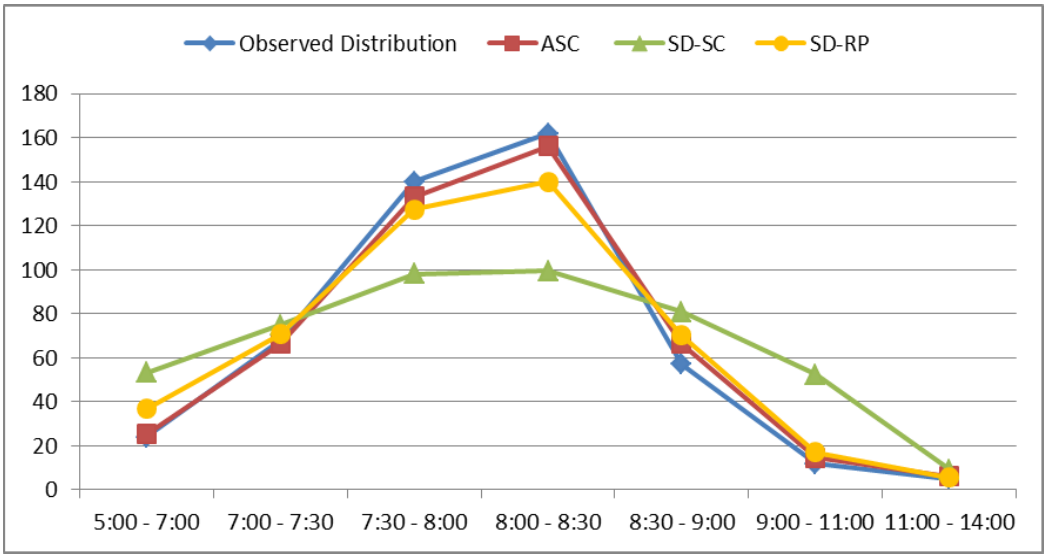

Figure 3 - Travel demand temporal distribution after congestion charging scheme: 30min

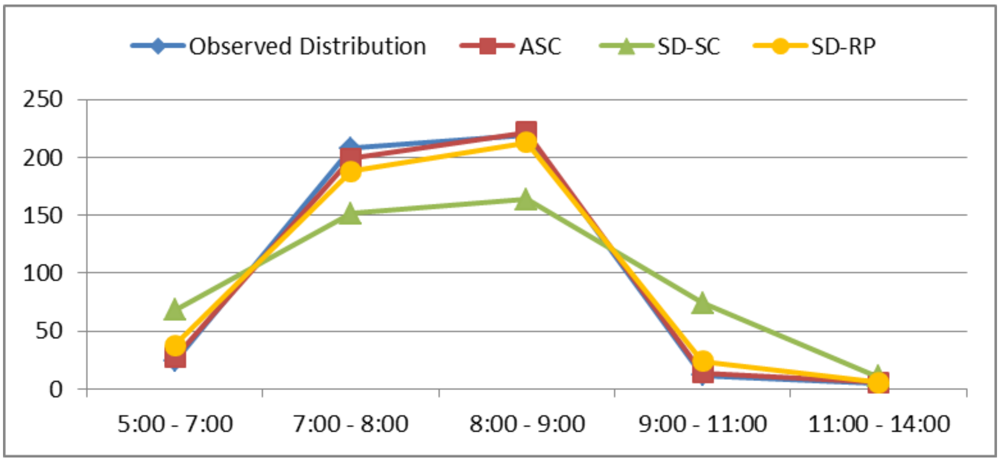

Figure 4 - Travel demand temporal distribution after congestion charging scheme: 60min

From these figures it can be inferred, first, that the forecasts generated by the ASC model differ slightly from the observed distribution. This was expected, as the ASC model replicates only the observed temporal distribution but it does not adequately explain temporal choices because it lacks the schedule delay terms.[9] Hence, the ASC model is less capable of forecasting TOD choice changes. Second, when more aggregate time periods are used, the difference between the SD-RP and ASC forecasts gets smaller. This means that the SD-RP model becomes less sensitive to trip departure time changes. Also, both the SD-RP and ASC model predictions tend to become more similar to the observed distribution when aggregate TOD intervals are used. This was partly foreseeable as when the TOD options are more aggregate there is more time difference between each of them, thus, it should be less attractive to change the trip departure time to a further away time period.

An interesting result is that the SD-SC model has a more horizontal and smooth distribution, which means that traffic is redistributed more equitably over time and that more people respond to the congestion charging scheme by travelling in the later periods of the morning. This is consistent with the objectives of the policies considered in the SC experiment (congestion charging and flexible working hour schemes) and it was expected because the SDE and SDL parameters in the SC environment are very similar.

Figure 5, on the other hand, shows the change in mode choice as a result of the implementation of the congestion pricing scheme (for the 15 min model only as the results for the other two models were very similar). The car-driving modal share reduces between 40 and 50%, while the rest of the modes increase their participation. Also, the difference between the results of the three models (SD-RP, SD-SC and ASC) is not as large as in the TOD choice, although the SD-SC model tends to produce smaller modal split changes.

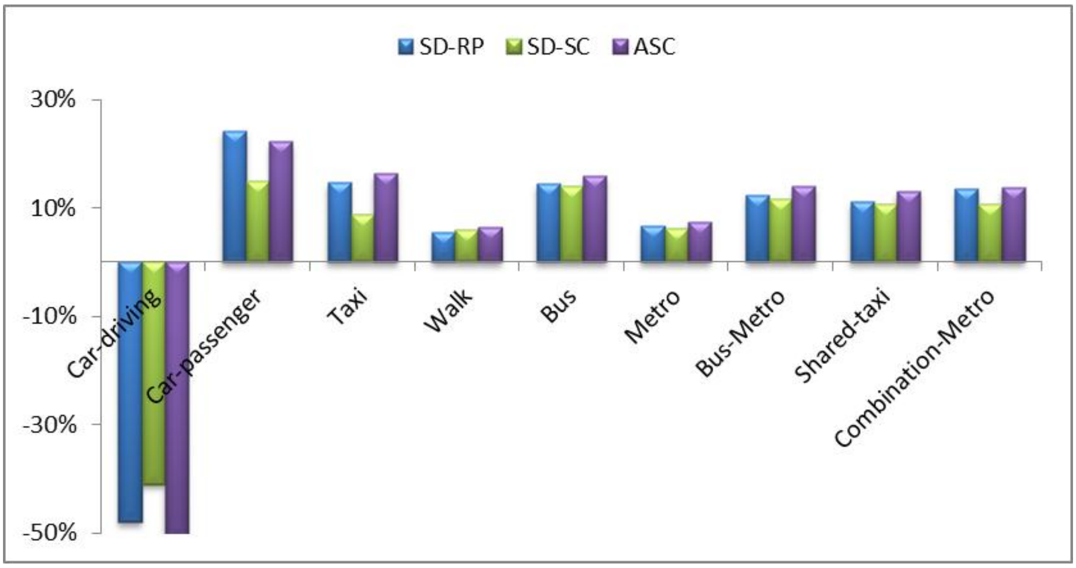

Figure 5 - Percentage change in mode choice after congestion charging scheme: 15min

[9] The $\bar{\rho}^2$ values are 0.21, 0.24 and 0.28 for the 15 min, 30 min and one hour models, respectively. This is a reduction of about 30% relative to the value for models with scheduling variables.

IMPLICATIONS FOR RESEARCH/POLICY

A simple forecasting exercise on the effects of a congestion charge scheme in Santiago, allowed us to conclude some implications regarding policy design. If Santiago transport authorities are evaluating the implementation of a congestion charge policy to mitigate the high levels of traffic observed in certain areas and periods of the day, a series of complementary actions are suggested; this so travellers have more high quality alternatives to travel to work (either transportation mode or time-of-day travel) when the charge is implemented.

The first recommendation to the authorities is to incentivize companies to install more flexible policies regarding the hours workers can arrive and depart work. If work schedule flexibility does not increase when a congestion charge is implemented in Santiago, it is possible that many car users will not change their trip departure times, therefore, traffic might not decrease as expected (such as what happened in the SD-RP curve in comparison to the SD-SC curve). Also it could cause greater dissatisfaction to car users with low work schedule flexibility levels (which in many cases coincide with low income people) as they would be obliged to pay the fee even though they could be willing to travel at other times to avoid the charge and/or congestion. An incentive for companies could be paying less taxes if they have a flexible working hours scheme.

As it was predicted, it is highly possible that many car drivers switch to other transportation modes when faced with a congestion fee. The second suggestion to transportation authorities is to invest the revenues derived from the congestion charging scheme into improving the transit system, both at the infrastructure and operational levels. Redirecting a major part of the funds into improving the public transportation system has the political advantage that it is the most popular compensation measure amongst Santiago residents in case of implementing a congestion charging scheme (see Salata et al., 2012). Also, if no investments are carried out in improving the transit service, the system might not be capable of handling the new demand generated, hence, declining the quality of the service. A good and recent example is the implementation of Transantiago, which doubled the demand the subway system faced from one month to another, which substantially decreased the comfort levels offered by the company. Also, another part of the congestion charge proceeds should be invested in modes that induce less congestion and air pollution, such as the bicycle, by building more bicycle lanes.

From a more technical point of view, our results can be useful to transport planners that are in charge of modelling the impacts of a congestion pricing scheme. If it is believed that a congestion charge policy would conduce to higher working flexibility, the SDE and SDL parameters from the SC choice utility functions should be used to predict its effects. If, on the other hand, it was expected that an insignificant change would occur in work flexibility, then the RP coefficients should probably be preferred. This is likely due to the fact that the SC experiment entailed the implementation of both a congestion charge and a working flexible hour scheme.

Other issues modellers should be aware of when using the model to predict are the changes in the values of time (in-vehicle, access and transfer) and trip departure choice when different time-resolution intervals (for example, 60min instead of 15 min) and cost coefficients (cost only, cost/wage only, or both together) are used. If the schedule delay parameters that proceed from the RP environment are used, it is preferable to use more disaggregate time intervals; whereas if the SC parameters are used there is not a big difference between the trip timing predictions made by the 15min, 30min and 60min models. Our results also show that replacing the SD variables with time-of-day ASC should be avoided when possible. Methodologies such as the one proposed by Kristoffersson and Engelson (2008), in which aggregate distributions of PAT are estimated with the use of a previously estimated TOD model (that uses the SDE and SDL variables) could be used.

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