Developing surveys for the study of departure time choice: a two-stage efficient design approach

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ABSTRACT

Departure time choice modelling has received renewed attention recently due to the increasing levels of congestion in many cities and the growing popularity of travel demand management (TDM) strategies such as road pricing. Current practice in evaluating the effectiveness of TDM policies usually incorporates the temporal dimension in transport planning models only through fixed factors derived from origin-destination data, making them unsuitable to predict demand at different times of the day properly. To mitigate these deficiencies, we argue in favour of estimating and applying specially formulated time-of-day choice models. Here we concentrate on the survey design generation process for obtaining suitable data to estimate such models, ensuring both realism and simplicity in the presentation; in particular, our SP exercise includes dependency between attribute levels. The proposed procedure should be widely applicable and offers a number of improvements over current practice in the field.

Keywords: *departure time choice; stated preference; time of day; travel demand management*

INTRODUCTION

The efficient implementation of transport demand management (TDM) strategies requires an in-depth understanding of travel behaviour. Mode, departure time, and route decisions are key choice processes that we need to understand to analyse the temporal and spatial dimensions of demand. Reductions in congestion can be achieved by spreading departure times into the 'shoulder' or off-peak periods, or by achieving a significant shift from private to public transport. Empirical evidence suggests that modifications in departure time are a more frequent strategy for avoiding congestion (or charging) as a result of TDM policies than changing mode [1-4], albeit that shifts in departure time still rank below route changes [5].

A better understanding of departure time choice is a crucial component for studying behaviour in congested networks, evaluating the effectiveness of transport policies [6] and planning the development or construction of infrastructure to accommodate projected demand.

In recent years, most studies concerned with departure time choice have made use of stated preference (SP) data and have been based on estimating scheduling models (SM). SP data are more popular in departure time modelling work than revealed preference (RP) data because the latter are difficult to obtain [7, 8] and require a rigorous and expensive data collection procedure, while also being affected by significant problems with inter-attribute correlations. However, there is no consensus regarding the design generation process for SP experiments in this context, ensuring both realism and simplicity in presentations to respondents. Two key issues in developing departure time choice experiments are (a) the dependence of some attribute levels on others within the same alternative [9]; and (b) that the design should be customised based on each specific respondent's trips and, therefore, common attribute levels may be inadequate in terms of experimental realism. The *aim* of this paper is to create a heuristic technique for designing an efficient SP exercise while addressing both issues above. To our knowledge, there are no reported applications of efficient designs with these features for departure time models in the literature.

The results reported in this paper are part of ongoing research, where this paper focuses mainly on survey design while reporting preliminary model results that are based on standard methods and thus do not yet take into account the full complexity of behavioural processes.

The remainder of the paper is arranged as follows. We first present a brief review of relevant literature regarding departure time choice models, looking separately at design features and modelling results. This is followed by a description of our survey work and the presentation of preliminary model results from the case study of Santiago. Finally, some conclusions and directions for further research are given.

LITERATURE REVIEW

Departure time choice models

The best known and most widely used departure time model is the Scheduling Model (SM) developed by Small [10]. It includes schedule delay (SD) terms, motivated by the earlier work of Vickrey [11], which represent the amount of time people arrive late or early at their destinations in comparison with their desired arrival times. The resulting model can successfully represent trade-offs between travel time and schedule delay terms, and can be written as follows:

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

where: $SDE_i = Max\{-SD_i, 0\}$ (2)

$SDL_i = Max\{0, SD_i\}$ (3)

$$d_L = \begin{cases} 1 \ if \ SDL_i > 0 \\ 0 \ if \ SDL_i = 0 \end{cases} \quad (4)$$

$$SD_i = Observed \ arrival \ time - Preferred \ arrival \ time \quad (5)$$

With this notation, the subscript *i* refers to alternatives (given by 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 travel time components have associated marginal utility coefficients that need to be estimated (defined as β_{TT}, β_{SDE}, and β_{SDL}), and we have an additional parameter to estimate in d_L, which is a penalty for arriving late at the destination (independent of the actual amount of lateness).

Good departure time models must consider travel time variability [12] and the duration of activities along with scheduling and associated levels of service information [12]. Daily activity participation time is relevant too due to its influence on trip making, the order of activity participation and trip departure time choice. Performing other activities during the day could impose restrictions on departure time choices, so it is ideal to consider tours to take into account possible relationship between different activities during the day.

De Jong *et al*. [13] and Hess *et al*. [7] reported SM including explicit penalties for decreased and increased activity participation time (PTD_i and PTI_i), and their generic utility function could be written as follows:

$$V_i = \beta_{TT} \, TT_i + \beta_C \, cost_i + \beta_{SDE} \, SDE_i + \beta_{SDL} \, SDL_i + \beta_{PTD} \, PTD_i + \beta_{PTI} \, PTI_i + \delta_L \, d_L \quad (6)$$

where: $PTD_i = Max\{-PT_i, 0\}$ (7)

$$PTI_i = Max\{0, PT_i\} \quad (8)$$

$$PT_i = Observed \ activity \ duration - Preferred \ activity \ duration \quad (9)$$

Departure time choices are not only determined by the factors discussed above but should consider employment characteristics, individuals' socio-economic characteristics, and information from other choices which may interact with time-of-day choice (e.g., route and mode choices), among others. This can be achieved through appropriate interactions with socio-demographic terms in the above specifications.

Design features of departure time choice experiments

Small *et al*. [14, 15] formulated a SM as part of a project to assess the value of travel time under congested conditions in America, and this model has since become the basis of many studies in the area,. They developed two designs to evaluate the trade-offs among: (i) travel time, variability, departure time, and cost, and (ii) cost, and congested/free flow travel time. Their sample was segmented based on travel times experienced by respondents to give more realism to the experiment. To evaluate model performance in forecasting, a wide range of coefficient values were used in simulation experiments.

Although the SM is the basis of most studies in the area, its reported design procedure does not enjoy the same acceptance and few studies have used it [16]. A wide range of different procedures have been used to obtain SP data for departure time modelling. Orthogonal in differences [17] and fractional factorial designs [18-20] are examples of standard design techniques used previously. Studies including a tour base approach have based their SP surveys on more complex designs, combining orthogonal and manual designs to account for a large number of attributes and levels [7, 13, 21].

Except for the simulation step within the design procedure by Small *et al*. [15], these design techniques do not use prior information about parameters. This absence of efficiency criteria in selecting attribute combinations potentially leads to larger sample size requirements. Recently, Koster and Tseng [9] developed a procedure including efficiency criteria in the design generation to address one of the most important difficulties associated with generating SM based choice experiments, namely that the variables used in the model are functions of the attributes shown to respondents in the survey rather than their actual values.

To achieve realistic choice experiments, the design procedure must also deal with (i) the potential dependency among different attribute levels of the same alternative, and (ii) the fact that choice situations should be personalised to each respondent's circumstances. Both of these issues can lead to difficulties in producing a design that has good statistical qualities for the entire sample.

Dependency, where attribute levels of alternative *j* are generated from those of a reference alternative *i*, can be accommodated in pivot designs [22]. However, additional complications arise when an attribute level within alternative *j* depends on another attribute level of the same alternative *j*, which in turn is also part of the design. This latter type of dependency is the one reported in this paper and is usually present in SM work. Not accounting for it (e.g. that travel time depends on departure time) can give rise to unrealistic choice situations, as can a failure to align scenarios with actual perceived possibilities in terms of realistic combinations from the respondent's perspective. While pivoting around current values can help in this context, customised levels must be carefully checked before applying the survey to avoid presenting unfeasible or irrelevant trade-offs to respondents. Occasionally, certain variation levels may not work well for the entire sample, as the differences postulated are too big or too small. For these reasons, we propose the inclusion of additional constraints to give even more realism to choice situations and avoid presenting 'meaningless' (from a respondent perspective) trade-offs.

SURVEY DESIGN

The procedure described in this section is a Bayesian efficient SP-off-RP step design that accommodates interdependence among attribute levels, and copes with the other above mentioned difficulties in these designs. It is important to note that a necessary condition for developing these designs is to have prior information and reference point schedule data on each respondent. This is commonly the case when collecting a specific sample for the sake of conducting an SP survey.

The procedure work as follows:

1. Definition of preliminary design features: This stage includes all activities prior to the development of an efficient design such as steps to:

   - Define the context of the experiment and the attributes to be presented;
   - Identify constraints and dependency among attribute levels;
   - Define first attributes to be optimised. In the case of SM, we propose to optimise shifts in departure/arrival time first;
   - Identify *a priori* coefficients;
   - Define the number of choice situations and, if necessary, blocks.

2. Optimisation stage to obtain SP generic designs: Since individuals face different choice situations, our approach generates a generic design containing attribute levels expressed as relative changes (percentages) from a reference point. If desired, this design can be common for all respondents although it is also possible to create different designs for several predefined segments within the population. This stage will optimise attribute levels without dependency relations and attribute levels that condition other attribute levels within the design. Within this phase, we need to:

   - Define efficiency and stopping selection criteria;

- Select a candidate SP design randomly or using heuristics, including constraints to avoid dominance among alternatives;
- Calculate probabilities and the asymptotic covariance matrix based on design attributes and *a priori* coefficients;
- Calculate design efficiency;
- Choose another SP candidate design until the stopping criterion has been reached.

3. Customisation of choice situations: here we move from a generic to a customised design for each respondent. The following activities should be performed:

   - Adapt choice situations using prior information (actual choice) and reference point schedule data; percentage variation levels in the generic design must be used to get customised attribute levels based on prior information and reference point schedule data;
   - Define non-optimised attribute base levels based on reported values or actual observations (e.g. travel time measurements, observed cost, etc.);
   - Include dependency constraints among attributes;
   - Include other constraints if necessary (e.g. thresholds for the difference between attribute levels)

4. Optimisation stage to obtain the final SP design: This step is similar to the second one but with two fundamental differences; (i) the attribute levels optimised at this stage are different from those optimised at step 2; (ii) at this stage, a full covariance matrix is computed from the total sample data, considering the customised attributes presented to respondents. Note that there is not a common design for all respondents, but a tailored design that contains as many rows as the number of participants times the number of choice situations per respondent.

5. Simulation experiment: The purpose of this stage is to test if the best design obtained above can recover a wide range of *"true"* coefficient values. The simulation must be done for the full sample.

6. Return to step 2 if the design does not allow recovery of a wide range of "*true"* coefficient values.

CASE STUDY

Departure time choice model for Santiago

Santiago is the capital and most important city of Chile. Its population is approximately 6 million inhabitants, living in an area of approximately 15,400 km^2. According to the 2001 Origin-Destination Survey [23], about 16.3 million journeys take place in Santiago every working day, most of them being radial (i.e. into the CBD in the morning and out again in the evening).

As a result of Chile's fast economic growth in the last 20 years, car ownership and motorised trip rates have increased substantially, causing congestion in the city at certain hours and locations. This has led to repeated consideration of TDM strategies by local authorities. The instrument traditionally used to both plan and evaluate changes regarding the city's transport system has been the strategic transport model for Santiago, ESTRAUS [24]. While this is a highly sophisticated model, its departure time module is based only on entropy maximisation principles [25]. Although ESTRAUS is recalibrated periodically using new mobility data, the departure time module has not been calibrated and its original formulation does not include important factors usually found in scheduling models such as activity participation and schedule delay measures.

The increased congestion and the forthcoming consideration of TDM strategies in Santiago motivated the development of our project to study departure time decisions in the context of transport project appraisal. A secondary aim of our research is to try to reduce the gap between the state of practice and the state of the art in this area, particularly in less developed countries.

Data

To develop a departure time choice model for Santiago, a three-step RP-SP-attitudinal survey was designed and applied to some 500 workers in the city. The first stage of the survey was a Computer Assisted Personal Interview (CAPI) at the workplace, which focused on collecting demographic and employment data, factors influencing scheduling decisions, and information about the schedule of planned activities for the following working day. At this stage, respondents did not have to report any trip they had done on the day of the first CAPI. The survey's second stage involved filling in a web page travel diary following an activity recall framework [26]. This travel diary was completed two working days after the first stage CAPI, and registered all trips completed before and after work, during the previous working day. Finally, the third stage involved another CAPI to collect responses to a SP-off-RP experiment along with an attitudinal questionnaire (both focused on work based trips). Information about respondents' income was also collected in this third stage.

This paper makes use of data from the SP-off-RP experiment designed using the procedure described above. Only people travelling by motorised transport modes and not transferring among public and private transport modes were included (359 of the 498 respondents). Two sets of SP experiments were presented sequentially to each respondent for evaluating re-timing and/or mode switching behaviour, considering work hour flexibility and the implementation of congestion charging. The first set of experiments focused on trips to work in the AM peak (Figure 1a), while the second looked at complete work tours comprising outbound and return legs (Figure 1b).

The motivation for our two-stage approach was twofold. Firstly, it allowed respondents to become used to answering hypothetical choice scenarios before facing the more complex tour based situations. Secondly, it allows us to study potential differences between behaviour in trip scenarios and tour scenarios.

In each scenario, respondents faced a choice between four alternatives, of which the first three were for journeys on the current mode departing at different times (namely travelling at early/ current/late time), while the fourth alternative offered the possibility of travelling by a different mode, but around the same time as for the originally reported trip. Public transport was the alternative mode for private transport users; if available, car was the primary alternative to transit users; if not, they were offered a new shared-taxi service. To minimise the impacts of inertia or reading left-to-right effects, the position of the re-timing alternatives was randomised across tasks for each respondent.

While the first experiment simply involves the choice between the four options, in the second SP, respondents had to make choices for both the outbound and return legs of the tour. This means that unless respondents decided to change mode, they had the possibility of choosing different alternatives for the outbound and return trips, generating a 10-alternative choice set as illustrated in Figure 2.

The main features within each step of the Survey Design procedure can be summarised as follows:

1. *Definition of preliminary design features*

Departure time, expected travel time, travel time uncertainty, cost and comfort were 5-level attributes, as shown in Table 1. It was decided to include travel time variability through the presentation of a *worst travel time experienced once a week* attribute instead of the more complicated five alternatives travel time presentation [27] because the main aim of the study was on departure time behaviour not on valuing travel time variability, and the more detailed approach would have unnecessarily increased complexity.

Cost and travel time were considered conditional on departure time, and levels of this attribute were optimised first during the second design stage. *A priori* travel time, comfort and cost parameter values were obtained from previous studies in Chile and SD parameters from international studies, which were then rescaled appropriately. As the second stage generic design contains attributes' relative changes from a reference point, *priors* were adapted by multiplying their original values by an attribute reference mean value.

2. *Optimisation stage to obtain SP generic designs*

A 50 row design with 10 blocks and a 40 row design with 5 blocks were adopted for the trip and tour questionnaire respectively, meaning that each respondent faced 13 choice situations. Separate designs were generated for private and public transport users and dominance restrictions were applied at this stage. Designs were selected following a mean Bayesian efficiency criterion (i.e. D_b-error) using NGENE (www.choice-metrics.com).

3. *Customised choice situations*

Attribute levels were customised using schedule and travel information collected in stages 1 and 2 of the survey respectively (RP component). The travel time levels used in the current timing alternative – the closest to the reported arrival and departure time at work – were obtained from the respondent's reported values in stage 2 of the survey. The travel times for the two re-timing alternatives and the mode-change alternative were obtained from GPS instrumented vehicles travelling at different times of the day during survey periods.

Base travel times were multiplied by generic design levels in each choice situation and were adjusted depending on changes in the departure time period, i.e. leading to bigger changes in more congested periods. In the case of retiming alternatives, 5 travel time variation levels (Table 2) were defined conditional on time-of-day periods and trip duration (with different levels if the usual trip took more than 50 minutes).

Travel costs were obtained by multiplying generic design levels by a time-period-specific cost base value defined in Table 2, to ensure that two alternatives travelling within the same period could not have different costs.

Larger departure time shifts implying departing before a reference time (6:00 am) were considered undesirable, and thus the multipliers were adjusted accordingly for people reporting travelling before 7:30 am using equation (10).

$$DT_{early} = DT_{reported} + DT\ shift_{early} \cdot \frac{(DT_{current} - Reference\ time\ )}{90} \tag{10}$$

Finally, a 5 minute threshold restriction on travel and departure time levels for different alternatives within a choice situation was included to ensure sufficiently large differences in attribute levels [28].

4. <u>*Optimisation stage to obtain the final SP design*</u>

Designs in this stage were selected randomly and evaluated according to a mean Bayesian efficiency criteria considering the full covariance matrix derived from the entire sample with data customised to each respondent. Uniform distributions and 150 random draws were adopted to allow for uncertainty in the *priors* (Table 3). This stage was coded in Visual Basic and the stopping criterion was fixed at 30 minutes running time without finding a better design. Designs were considered satisfactory only if recovering *a priori* parameters in the simulation. We also evaluated the performance of this design compared to orthogonal and efficient designs without dependency constraints using simulation. This design had more success recovering initial assumed parameters than the other two designs.

Estimation results

After data cleaning, a total sample of 274 respondents was used in the estimation process. Design efficiency loss can be expected as a certain level of non-response led to differences between the estimation sample and the sample used in the last stage of the design generation process, which used a full covariance matrix derived from a sample of 359 respondents.

Most respondents (98%) work at least 40 hours/week in workplaces located within or near the city centre. A large share (62%) of the sample consists of transit users, most of them being Metro or Bus users.

For trip data the following generic model was used:

$$V_i = ASC_i + \beta_{TT}\, TT_i + \beta_{Time\_diff}\, Time\_diff_i + \beta_C\, cost_i + \beta_{SDE}\, SDE_i + \beta_{SDL}\, SDL_i \quad (11)$$

Time_diff stands for the difference between "worst" and "best" possible travel times normalised by the "best" travel time presented in each alternative. All other remaining variables are those defined for equations (1)-(5) with subscript *i* indexing the 4 alternatives in the trip data. The d_L constant was not significant and was removed from the model.

For tour data modelling, to link trips before and after work, an activity participation penalty was introduced as proposed by de Jong et al. [13] and Hess et al. [7]. Here the generic model can be written as equation (12).

$$V_i = ASC_i^{outbound} + ASC_i^{return} + \beta_{TT}\, TT_i + \beta_{Time\_diff}\, Time\_diff_i + \beta_C\, cost_i + \beta_{SDE}^{outbound}\, SDE_i^{outbound} + \beta_{SDL}^{outbound}\, SDL_i^{outbound} + \beta_{PTD}\, PTD_i + \beta_{PTI}\, PTI_i \quad , \quad (12)$$

where PTD_i and PTI_i are defined in equations (7)-(9). Separate constants for outbound and return legs can be used across alternatives to capture general preferences for departing at specific times or on specific modes for either leg. The attributes *TT*, *Time_diff* and *Cost* refer to both legs while *SDE* and *SDL* are outbound specific (return-specific values cannot be included in a model which also has activity duration values). Subscripts *i* in this model represent the ten available alternatives.

From the above generic formulations, MNL models were estimated in BIOGEME[29], where the repeated choice nature of the data was accommodated in the calculation of standard errors by using the panel specification of the *sandwich matrix*. In addition to the trip and tour models, a joint model was also estimated, allowing for scale differences between both games. A likelihood ratio test allowed us to confirm that the null hypothesis required by the joint model (i.e. it is equivalent to the two separate trip and tour models) cannot be rejected (χ^2 of 7.09 against a critical value χ^2=11.07 for 5 degrees of freedom at the 95% level). Travel time values (VOT), willingness to pay (WTP) for different attributes and *trade-off ratios* (TOR) against the travel time coefficient were calculated. The estimation results are shown in Table 4.

All estimated coefficients have the expected sign and are significant at the 95% confidence level, except for the travel time coefficients in the tour and joint model. It should be noted that these coefficients maintain their correct signs and in the case of the joint model, the parameter is significant at the 90%. level To some extent, less significant travel time parameters are expected in models estimated from this kind of exercise as workers could be more worried about travel time uncertainty than differences in their usual travel times. Indeed, pre-tests and three focus groups showed that workers preferred to avoid highly uncertain work journey durations due to the necessity of meeting work schedules.

The trip game seems to have been more successful in retrieving meaningful and significant estimates, possibly due to its lower complexity, than the tour experiment. However, the tour model has the added value of including activity participation time penalties, different constants for each trip and provides a richer framework where respondents can take into account the influence of their choice on other activities during the day, as they will have a more complete picture of trips related to the activity that is being modelled.

In general terms, people prefer arriving earlier rather than later at their work places, and are more worried about meeting schedules in the morning – the constants for retiming are more negative for outbound trips. Trip model estimates indicate that if attributes among alternatives are kept equal, people are more likely to change their departure time than to travel by a different mode, in line with previous findings by de Jong et al. [13], and Hess et al. [2, 7]. On the other hand, the tour and joint models show that while the sensitivity to early departure is lower than that to changing mode, this is not the case for late departure.

Values of time estimates are similar among different models and in line with values commonly used in Chile. Schedule delay values are in line with earlier international departure time studies where people assign greater penalties for arriving later than earlier. Respondents are willing to pay approximately Ch$ 8/min more (about US$ 1/hr) for arriving a minute closer to their desired work arrival time. A surprising result from the tour and joint models is that people prefer staying longer rather than shorter at their workplaces to avoid congested or more expensive travel periods.

Trade-off ratios relative to travel time for SDE and SDL are in line with those reported by Li et al. [27] and de Jong et al. [13]. However, the ratios for decreased and increased time at work (PTD and PTI ratios) are much higher than values previously reported by Hess et al. [7] and de Jong et al. [13]. Furthermore, dividing the marginal utility of extra time experienced once a week (i.e. the parameter for the difference in travel times divided by the mean usual travel time) by the marginal utility of cost (i.e. the cost parameter) gives us the WTP for reducing extra time experienced once a week. This gave the result that every extra minute over the usual travel time is valued between 32% and 75% over the usual travel time depending on the model. These values can also be viewed as a measure of reliability/variability of travel time and are in line with Small et al. [30].

CONCLUSIONS AND FUTURE WORK

We have presented a procedure for designing realistic SP exercises for departure time choice modelling including dependency between attribute levels. The methodology highlights some of the complexities associated with departure time choice experiments and should be useful in guiding practitioners in developing experiments to collect appropriate data for transport planning. Our procedure should be widely applicable and offers a number of improvements over current practice in the field.

An application of our SP design to a sample in Santiago was also presented. The aim of the experiment was to evaluate trip timing decisions when congestion charging and flexible work hours are implemented. Trip, tour and joint trip-tour models were estimated indicating that people in Santiago do indeed modify their trip timing decisions when congestion rises and TDM strategies are implemented. Results are in line with findings in developed countries where modelling departure time choice is an extended practice, suggesting that advanced methods applied in developed countries can also be effective in emerging economies.

We acknowledge that the full complexity of the behavioural processes will undoubtedly require the use of more advanced models that allow mixing different kinds of data (RP and attitudinal data) and incorporate different factors and dimensions influencing the trip timing choice. *Trade-off ratios* reported in this paper should be treated with caution as the models reported do not incorporate the full complexity of the behavioural process and the possible heterogeneity in respondents' preferences. This could also help to better explain the differences in sensitivities across attributes. Indeed, we computed tests to evaluate the significance of the differences between the parameters of *SDE, SDL* and *TT* and could not find significant differences between the parameters of *SDE* and *SDL* for all models. In the joint model, the difference between the parameters of *SDE* and *TT* was not significant but that between the parameters of *SDL* and *TT* was clearly significant (p=0.027). Our next step will be to incorporate more socioeconomic and employment data information to these models using a joint RP-SP-attitudinal model.

Finally, it seems appropriate to mention a couple of weaknesses that should be addressed in future work. Although collected in our survey, our models do not include other possible responses to variations in travel conditions that could have impacts on travel behaviour, such as trip chaining, working at home, and not working. The focus here was on presenting an SP procedure to design surveys with a view to collecting data for the development of advanced departure time choice models for transport planning and to give preliminary results based on this procedure; inclusion of these models in a broader regional travel demand model is beyond the scope of this paper. In practice, a model of the type developed here would be used in a forecasting system that uses a synthetic population as input, and assumptions about preferred arrival times and preferred durations would have to be made, e.g. through an appropriate random distribution.

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LIST OF TABLES AND FIGURES

(a) Questionnaire considering only the AM trip to work

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

(b) Questionnaire considering the complete tour to and from work

Choice Situation: 2	Option A	Option B	Option C	Alternative mode
Departure time to work	7:21	8:11	9:06	8:15
Usual travel time to work (Usual arrival time to work)	44 (8:05)	54 (9:05)	49 (9:55)	40 (8:55)
Travel time to work once a week (Usual arrival time to work)	49 (8:10)	62 (9:13)	56 (10:02)	48 (9:03)
Comfort	Crowded vehicle, sitting	Crowded vehicle, standing, usually have to wait next for boarding	Crowded vehicle, sitting	
Adittional cost ($)	$ 527	$ 561	$ 493	$ 1,500
¿Which option would you choose?	■	■	■	
Departure time from work	17:00	18:00	18:45	18:10
Usual travel time at destination after work (Usual arrival time at destination after work)	40 (17:40)	56 (18:56)	49 (19:34)	40 (18:50)
Travel time at destination after work once a week (Usual arrival time at destination after work)	55 (17:55)	65 (19:05)	54 (19:39)	51 (19:01)
Comfort	Crowded vehicle, sitting	Crowded vehicle, standing	Half crowded vehicle, standing	
Adittional cost ($)	$ 434	$ 527	$ 561	$ 1,200
¿Which option would you choose?	■	■	■	■

52% Previous Next

FIGURE 1. Illustrative SP choice screens for both questionnaires
(original was in Spanish and cost were in Chilean pesos. Ch$ 500 = 1 US$)

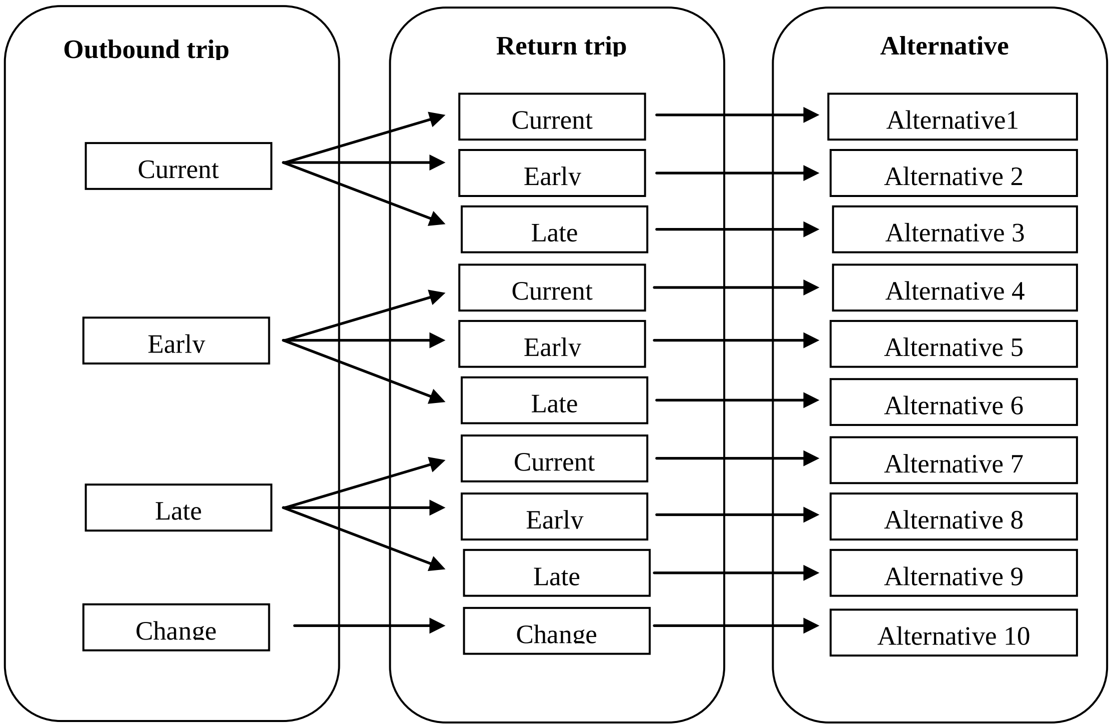

FIGURE 2. Available alternatives in tour models

TABLE 1. Attribute levels and *priors* for stage 2 generic design

Attribute	Levels					Prior	
	1	2	3	4	5	Min	Max
Travel time change (fixed across alternatives)	1	1.05	1.1	1.15	1.2	-7	-0.7
Current - Departure time change	-10	-5	0	5	10	-	-
Earlier - Departure time change	-30	-45	-60	-75	-90	0.01	0.24
Later - Departure time change	30	45	60	75	90	-0.36	-0.015
Car travel time variability	0.1	0.15	0.2	0.25	0.3	-9	-0.3
Public transport travel time variability	0.15	0.2	0.25	0.3	0.35	-9	-0.3
Cost (fixed across alternatives)	0.7	0.85	1	1.15	1.3	-0.3	-0.017
Comfort	0.7	0.85	1	1.1	1.2	-1.5	-0.85

TABLE 2. Travel time variation levels for retiming alternatives and cost base values (in Chilean pesos)

Travel time variation levels

Alt.	Levels	Trip duration < 50 min					Trip durationn > 50 min				
		1	2	3	4	5	1	2	3	4	5
Earlier	Period1	0.8	0.85	0.9	0.95	1	0.9	0.92	0.94	0.96	0.98
	Period2	0.7	0.75	0.8	0.85	0.9	0.8	0.85	0.9	0.95	1
	Period3	0.55	0.6	0.65	0.7	0.75	0.7	0.8	0.85	0.9	0.95
	Period4	1.02	1.04	1.06	1.08	1.1	1.02	1.04	1.06	1.08	1.1
	Period5	1	1.05	1.1	1.15	1.2	1	1.05	1.1	1.15	1.2
Later	Period1	0.8	0.85	0.9	0.95	1	0.9	0.92	0.94	0.96	0.98
	Period2	0.7	0.75	0.8	0.85	0.9	0.8	0.85	0.9	0.95	1
	Period3	0.55	0.6	0.65	0.7	0.75	0.7	0.8	0.85	0.9	0.95
	Period4	1.05	1.1	1.15	1.2	1.25	1.02	1.04	1.06	1.08	1.1
	Period5	1.25	1.3	1.35	1.4	1.45	1	1.05	1.1	1.15	1.2

Cost base values (in Chilean pesos)

Time period	-6:30	6:30-7:00	7:00-7:30	7:30-8:00	8:00-8:30	8:30-9:00	9:00-9:30	9:30-10:00	10:00-10:30	10:30-
Private	$500	$800	$1000	$1200	$1500	$1500	$1200	$1000	$800	$500
Public	$510	$560	$620	$660	$660	$620	$580	$560	$540	$510

TABLE 3. Priors used in final optimization process

Attribute	Travel time	SDE	SDL	Cost	Comfort
Max	-0.012	-0.0072	-0.0144	-0.00017	-0.00038
Min	-0.12	-0.24	-0.36	-0.003	-0.00666

TABLE 4. Estimation results for trip, tour and joint trip-tour models

	Trip model		Tour model		Joint model	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Alternative specific constant						
Change mode	-1.11	-8.91	-0.625	-4.3	-0.628	-5.21
Current departure time – trip	-	-	-	-	-	-
Current departure time - outbound	-	-	-	-	-	-
Current departure time – return	-	-	-	-	-	-
Early departure time - trip	-0.719	-3.39	-	-	-0.345	-2.78
Early departure time – outbound	-	-	-0.574	-2.77	-0.684	-3.76
Early departure time – return	-	-	-0.421	-2.64	-0.486	-3.49
Late departure time – trip	-0.917	-4.41	-	-	-0.512	-3.69
Late departure time – outbound	-	-	-1.73	-7.29	-1.76	-8.28
Late departure time – return	-	-	-1.21	-6.94	-1.16	-7.23
Cost (β_C)	-0.0006	-3.5	-0.0002	-2.17	-0.0003	-2.87
Schedule delay early in minutes (β_{SDE})	-0.0175	-4.78	-0.014	-3.48	-0.011	-4.04
Schedule delay late in minutes (β_{SDL})	-0.0233	-6.25	-0.0134	-2.82	-0.0133	-4.48
Travel time (β_{TT})	-0.0157	-1.95	-0.0063	-1.21	-0.0076	-1.75
Difference in travel times (β_{time_diff})	-1.33	-2.95	-0.819	-3.25	-0.798	-4.03
Decreased work time penalty (β_{PTD})	-	-	-0.0126	-4.28	-0.0121	-4.49
Increased work time penalty (β_{PTI})	-	-	-0.0054	-2.53	-0.0064	-3.59
Scale factor - over trip data	-	-	-	-	1.76	8.28
Willingness to pay (Ch$/min)						
VOT	25.78		28.81		27.83	
SDE	28.74		63.93		40.44	
SDL	38.26		61.19		48.90	
Time-diff (Extra time experienced once a week)	45.08		37.90		39.89	
PTD	-		57.53		44.49	
PTI	-		24.84		23.57	
***Trade-off ratios* versus travel time coefficient**						
SDE	1.11		2.22		1.45	
SDL	1.48		2.12		1.76	
Time-diff (Extra time experienced once a week)	1.75		1.32		1.43	
PTD	-		2.00		1.60	
PTI	-		0.86		0.85	
Number of estimated parameters	8		12		15	
Number of observations	1370		2246		3616	
Number of individuals	274		274		274	
Final log-likelihood	-1450.46		-4089.17		-5543.58	
Log-likelihood ratio test (α=0.05, df=5)					7.9 ($\chi^2_{0.05;5}$=11.07)	