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Subjective valuation of the transit transfer experience: The case of Santiago de Chile

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ABSTRACT

The still controversial *Transantiago* public transport system, in Santiago de Chile, has a topological structure that often requires its users to make one or more transfers to reach their destinations. This was rarely necessary in the previous non-integrated system and users reacted with unexpected displeasure when it started even though fare integration in the new system means that transferring involved no extra costs. This study investigates users' subjective valuations of the transfer experience and its associated elements (walking and waiting times), analysing how these vary for different types of transfer combinations. In particular, we determine the relative preferences the following transfer combinations: metro–metro, metro–bus, bus–metro and bus–bus, with emphasis on the importance of various physical characteristics such as information availability, the existence of station escalators and the ability to board the first available bus or train. We also estimate the relative valuation of the different time component values (walking, waiting and in-vehicle) of trips including a transfer, and also derived the penalties users assign to trips that require transferring at intermodal stations during the morning peak hour. The trip time components most heavily penalised were the walking time involved in transferring and the final walking time to the user's destination.
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1. Introduction

Transfers between different public transport modes or lines are a significant structural element in integrated urban transit systems, the topological designs of which typically combine a trunk network of high-frequency and high-capacity services, with a secondary feeder network of lower frequency and lower capacity services. In such systems, transferring is often necessary when travelling across different zones. The advantage of this design is that it optimises resources while reducing congestion and pollution, but it comes at the price of forcing many users to change modes or lines at some point on their journeys.

Despite the obvious importance of the transfer phenomenon not many studies appear to have addressed it in the past (CTPS, 1997; Liu et al., 1997; Wardman et al., 2001). More recently, a thesis by Crockett (2002) analysed the willingness of transit users to transfer as a function of different service levels, network information, security and waiting times in a non-integrated system comprising an urban rail network and buses in the city of Chicago. Guo (2003) added user-assigned penalties to transfers based on travel and walking times within the rail network serving central Boston. Espino et al. (2007) identified and analysed users' preferences over various transfer alternatives for urban and interurban travel on non-fare-integrated bus lines and examined their willingness-to-pay (WTP) for a direct trip. Finally, Guo (2008) studied transit systems planning and its effect on modal split in Boston's interurban/commuter rail network and the London Underground. No further work was found despite a thorough review of the literature.

The principal objective of this paper is to present a critical analysis of the various elements of transferring that matter to passengers on peak-hour journeys. Using data from *Transantiago*, the radically new and quite controversial public transport system serving Santiago de Chile (Muñoz et al., 2009), we set out to determine the most relevant variables in the transfer experience and their relative weights, and the associated user time valuations (walking, waiting, in-vehicle travel), placing particular emphasis on the physical characteristics that users transferring must face. An essential element of our work was the creation of a data bank from information gathered through a stated choice (SC) survey. This was constructed using an efficient design methodology under a Bayesian parameter estimation framework (Rose and Bliemer, 2009).

The remainder of this paper is organised as follows. Section 2 describes the theoretical background of our study; Section 3 describes the experiments conducted, the design and application

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of the SC survey, the proposed models and the analysis of the results they generated; finally, Section 4 presents our main conclusions.

2. Methodological background

2.1. Discrete choice modelling

Random utility theory postulates that individuals (q) choose among different alternatives (A_j) on the basis of their utility U_{jq}. The modeller, an observer of the system, knows only some of the elements considered by the individual (indeed, this means that some individual choices often cannot be explained) and is forced to assume that the individual's utility has two elements: first, a representative utility function V_{jq}, which is considered linear in its parameters in the simplest version of the theory (i.e. assuming compensatory behaviour):

$$V_{jq} = \sum_k \theta_{jk} X_{jkq} \tag{1}$$

where θ are the parameters (marginal utilities) to be estimated and $\boldsymbol{X}$ are attributes of the alternatives or socioeconomic characteristics of the individuals as observed by the modeller. The second element is a random error term ε_{jq} such that:

$$U_{jq} = V_{jq} + \varepsilon_{jq} = \sum_k \theta_{jk} X_{jkq} + \varepsilon_{jq} \tag{2}$$

If the errors distribute identically and independently (iid) Extreme Value Type 1, the probability that individuals q choose alternative A_i from their available choice sets $A_{(q)}$ is given by the multinomial logit (MNL) model (see Domencich and McFadden, 1975):

$$P_{iq} = \frac{\exp(\beta V_{iq})}{\sum_{A_j \in A_{(q)}} \exp(\beta V_{jq})} \tag{3}$$

where β is a non-identifiable scale factor that has to be normalised. This model is readily estimated using the maximum likelihood method, which yields the set of parameters that is most likely to replicate the observed sample (Ortúzar and Willumsen, 2011). Unfortunately, the MNL model has significant limitations, such as assuming that the alternatives are mutually independent (the independence of irrelevant alternatives property), that the utility functions of the alternatives are homoscedastic, that all sampled individuals have the same tastes (i.e. equal θ_{ik}) and that all observations are independent. If any of these restrictions is not satisfied, the model may produce biased results.

The mixed logit (ML) model, on the other hand, is capable of a much more general representation because it can be extended to handle situations with correlation between alternatives, heteroscedasticity, taste variations and repeated observations of individuals (i.e. panel effect). Two specifications of the ML model have been posited: the random parameters logit (RPL) and the error components logit (ECL). The first has a very similar structure to an MNL model except that the parameters θ, instead of being fixed for all individuals, are distributed over the population. This characteristic allows the differences in individual tastes for the various utility function attributes to be easily modelled. The RPL is given by the following structure (Train, 2009):

$$U_{jq} = \sum_k \overline{\theta}_{jk} X_{jkq} + \sum_k \gamma_{qk} X_{jkq} + \varepsilon_{jq} \tag{4}$$

where $\overline{\theta}_{jk}$ represents the population mean for the kth attribute and γ_{qk} its standard deviation. These two are used to construct a parameter θ_{jkq} that represents the individual marginal utility for attribute k of alternative j.

The error components (ECL) specification, on the other hand, consists basically in adding an error term η_{jq} to the traditional random utility formulation in Eq. (2) that can be distributed as the modeller sees fit. This model is structured very generally as follows:

$$U_{jq} = \sum_k \theta_{jk} X_{jkq} + \varepsilon_{jq} + \eta_{jq} \tag{5}$$

However, estimating any type of ML model is considerably more complex than estimating a MNL given that the former's probability function is not a closed analytic expression such as Eq. (3) but rather the integral of a probability function (MNL or some other function if so desired) over the range of variation of the parameters. To solve the multivariable integral and find the model's best estimators, the simulated maximum likelihood method is most commonly employed (Godoy and Ortúzar, 2008), but the model can also be estimated using a Bayesian approach (Train, 2009).

2.2. Willingness-to-pay estimation

A variety of methods are available to estimate the WTP for improving an attribute X_{jk} and their complexities are many, but all have in common that they require an attribute related to the price or direct cost of the good or service in question.

For MNL and ECL models with linear utilities such as Eq. (1), the WTP formula is

$$WTP(X_{jk}) = \frac{\theta_{jk}}{\theta_{jc}} \tag{6}$$

where θ_{jk} is the parameter of the attribute for which WTP is being estimated and θ_{jc} is the cost parameter (Jara-Díaz, 2007). But the values in Eq. (6) are based on point parameter estimates which, even in the relatively simple MNL case, have an asymptotically Normal distribution (as they are maximum likelihood estimators). To circumvent this problem Armstrong et al. (2001) proposed the following simple and highly efficient method of finding the WTP confidence interval:

$$\Delta WTP(X_{jk}) = \left(\frac{\theta_{jk}}{\theta_{jc}} \frac{t_c}{t_k}\right)\left(\frac{(t_c t_k - \rho t_\alpha^2)}{(t_c^2 - t_\alpha^2)} \pm \frac{\sqrt{(\rho t_\alpha^2 - t_c t_k)^2 - (t_k^2 - t_\alpha^2)(t_c^2 - t_\alpha^2)}}{(t_c^2 - t_\alpha^2)}\right) \tag{7}$$

where t_k and t_c are the respective t-test values for θ_{jk} and θ_{jc}, t_α is the tabulated critical value for a confidence level α and ρ is the correlation coefficient between the two parameters. The estimation of WTP for RPL models is much more complex. The interested reader may wish to consider the discussion in Sillano and Ortúzar (2005).

2.3. Stated choice survey

Stated choice (SC) surveys are a powerful modelling tool, particularly in cases where the individuals surveyed cannot be confronted with the real-life situation under study. In this type of survey individuals can be queried on a number of different choice situations, yielding various responses per respondent, with the consequent savings in costs compared to revealed preference (RP) surveys which normally produce only a single answer per respondent. However, with SC data in MNL models we would be forced to assume that the responses of each individual to different choice situations are independent, and for many years this problem was ignored in the literature (see Ortúzar et al., 2000). A relatively simple solution to this problem is to estimate ML models using an error component to correlate the responses of each respondent.

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