Integrating Revealed Preference and Stated Response Data into a Jointly Estimated Hierarchical Discrete Choice Model

David Hensher
Professor of Management
and Director, Institute of Transport Studies
University of Sydney

Abstract:

Revealed preference and stated response data have both contributed to the development of the literature on behavioural travel demand modelling. Until very recently, these two types of data have been independently used in the estimation of a wide variety of discrete choice applications in transport. There is growing interest in exploring the view that both types of data have useful information and that their integration will improve the overall explanatory power of choice models.

In this paper, we present the theoretical framework for combining the data sources, and specify a model capable of introducing the two data sets with independent choice outcomes. The approach requires the application of a full information maximum likelihood estimation procedure of the hierarchical logit form. We demonstrate the advantages of the dual data strategy by comparing the results with those obtained from models estimated independently with RP and SR data. Data collected as part of the pre-feasibility study of the Very Fast Train Project is used to estimate a set of illustrative mode choice models.

Contact Author:

Professor David A Hensher
Institute of Transport Studies
Graduate School of Business
The University of Sydney NSW 2006

Telephone: (02) 550 8631 Fax: (02) 550 4013

Introduction

As the travel demand modeller acquires a greater awareness of the complexity of the decision making process underlying traveller behaviour, a natural scientifice instinct is to seek out new paradigms capable of adding to the stock of knowledge on how such decisions are made and how choice outcomes are predicted by the analyst. A recognition that disaggregate analysis data at the level of the decision making unit provides an opportunity to fully explore the possible sources of variation in travel behaviour has spawned a huge literature since the late sixties. In the last 10 years one noticeable "division" has taken place in the specification of the source of data capable of eliciting information on preferences and choices.

Revealed preference (RP) data, the mainstay of econometric modelling and stated preference (SP) data, pivotal data in psychometric and market research modelling, have been separately used in the analysis of a large number of individual preference/choice studies (e.g. Hensher et.al. 1988, Batsell and Louviere 1991). The recognition of the relative strengths and weaknesses of both types of data suggested that the joint utilisation of both data should enrich the modelling activity and further our understanding of traveller behaviour. Whereas RP data describes actual choices in terms of a set of market-based measurements of attributes of alternatives (which by definition are restricted to the currently available feasible set), the SP data describe potential choices in terms of a set of constructed measures of combinatorial mixes of attributes of real and/or hypothetical alternatives. The opportunity to position an SP data set relative to an RP data set within the one empirical analysis on the common choice problem enables the modeller to extend and infill the relationship between variations in choice response and levels of the attributes of alternatives in a choice set, and hence increase the explanatory power of the choice model.

With this motivation in mind, this paper outlines one method of integrating two types of data with different properties which are complementary ways of investigating the same choice problem. The paper is organised as follows. We outline the theoretical and econometric issues which control the way in which two data types can be combined for empirical choice modelling. An illustrative application, based on the pre-feasibility mode choice data for the Very Fast Train Project is then described, followed by a discussion of the procedure required to estimate a hierarchical logit model based on both RP and SP data. The empirical results show the potential benefits of mixed preference/choice data.

The Theoretical Emphasis

An individual traveller when choosing amongst a set of mutually exclusive alternatives is assumed to identify the set of attributes relevant to the personal decision calculus, and will impose implicit weights on each attribute to arrive at a choice. The socioeconomic characteristics of the traveller will have a conditioning influence on both the attribute weights and the determination of the feasible choice set. Although the individual decision maker knows precisely, although subconsciously, the decision calculus and the set of attributes used in arriving at a choice outcome, the analyst is not privy to this level of detail. Consequently the analyst has to try and explain the observed choice outcome, be it based on a market observation or a response to a stated choice experiment, with a

component of the knowledge available to the traveller summarised by an index of the unobserved influences.

In linking the observed and unobserved sets of attributes associated with each alternative to the choice outcome, it is accepted practice that individuals act as if they are maximising utility subject to a set of constraints. These constraints may be financial, temporal or physical. The solution to the utility maximisation problem is an indirect utility expression for each alternative which is a function of the observed and/or measured attributes of an alternative, a set of socioeconomic characteristics which are proxies for some of the unobserved attributes of an alternative, and a random effect to represent the residual set of unobserved attributes of the alternatives.

The behavioural framework outlined is applicable for both RP and SP data. The definition of the observed and unobserved influences on the choice outcome however varies. First, the observed levels of the attributes of alternatives typically obtained in an RP study are sought directly from the traveller. The responses are reported perceived levels, which may vary from the "actual" levels. By contrast, the attribute levels associated with an SP study are fixed by the analyst, and are by definition "actual" levels. Thus we have at least one source of variation in the metric of the observed attributes of alternatives. Second, the choice outcome in the RP study is the known outcome, whereas for the SP study it is the potential outcome or the outcome with the highest likelihood of occurrence given the combination of attribute levels offered in an experimental replication. Third, the SP study elicits choice responses from a repeated measures experiment in which the attribute levels (and even the choice set) are varied, in contrast to the single response in an RP study. Thus there is a greater amount of information on traveller response to a range of possible attribute profiles.

After recognising the sources of observed variation between RP and SP data, the remaining unobserved sources of indirect utility are most unlikely to display identical distribution profiles within the common sampled population. Hence the "naive" pooling of the two types of data cannot be treated as if they display identical unobserved effects. Given that the variance of the unobserved effects is an important piece of information used in the derivation of the functional form of a probabilistic choice model, this variance deviation has to be recognised and accommodated. One solution is to scale the variance of the unobserved effects associated with the SP data so that the equality of variances across the RP and SP components of a pooled model is reinstated. A priori the relative magnitudes of the variances is unknown, due to the many sources of differences between the RP and SP contexts. The equality of variances is a permissable empirical outcome, but not one to be assumed ex ante.

The Econometric Specification

The distribution of the unobserved effect in an indirect utility expression has always been an important consideration in econometrics. Within the family of random utility models centred on discrete choices, the multinomial logit (MNL) form requires that the unobserved effects are independently and identically distributed (IID) across the alternatives in the choice set, according to the extreme value type I distribution (Hensher and Johnson 1991, Borsch-Supan 1986, Ben-Akiva and Lerman 1985). The violation of this constant variance condition (alternatively referred to as the independence of irrelevant alternatives property) resulted in the development of the nested (or hierarchical) logit (NL) model, which permitted differential variance between levels and/or branches within a level of the nested structure but a common variance within a branch (Hensher 1986, 1991, Borsch-Supan 1986). The explicit accommodation of differential variance within a nested-logit model provides the econometric framework for incorporating RP and SP data in a single empirical choice model.

In order to scale the variance of the unobserved effects in the SP component relative to the RP component, it is necessary to simultaneously estimate the hierarchical structure. This requires estimation using the method of full-information maximum likelihood (FIML). Sequential estimation of a nested logit model, which is more common due largely to the availability of software (such as BLOGIT and LIMDEP6.0), is unable to impose the scale condition across the tree structure to accommodate the ratio of the variances of the unobserved components of indirect utility associated with the RP and SP data. The scaling factor, equal to the ratio of the variance of the unobserved RP effect to the variance of the unobserved SP effect can be identified as the estimated parameter of the inclusive value derived from the SP choice component, constrained across all SP alternatives (Bradley and Daly 1991). It is well known that the parameter estimate associated with the inclusive value variable estimated in an upper level of a tree (with the inclusive value variable derived from the choice process in the lower level of the tree) is inversely related to the variance of the unobserved effect (Williams 1977).

The joint estimation of a choice situation using two types of data involves a choice outcome associated with the RP data and a number of choice outcomes associated with the SP data. This is not a typical discrete choice application where there is only one choice outcome in either an MNL or NL configuration. To allow for this multiple response we have to "stack" the observations in such a way that for each RP observation there is a null choice set for the SP observation, and for each SP observation there is a null choice set for the equivalent RP observation. Furthermore we have to structure the hierarchical tree in such a way to obtain the parameter estimate for inclusive value. The structure is given in Figure 1. This structure guarantees that each of the parameter estimates associated with the SP data are scaled by the ratio of the varainces. The inclusive value associated with the SP branches provides the empirical information on the scale factor.

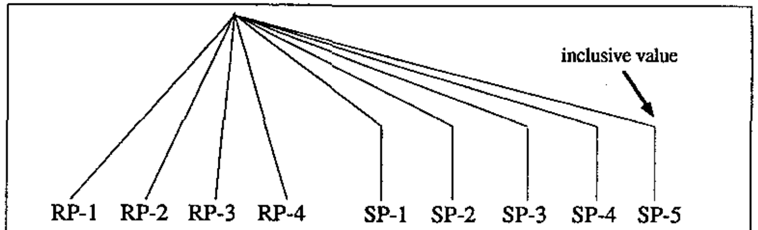

Fig 1. The Estimation Structure

The Empirical Illustration

The data used to illustrate the application of the approach are drawn from the pre-feasibility market study associated with the Very Fast Train (VFT) project. We have extracted 118 surveys of 1986 non-business travel between Sydney, Canberra and Melbourne. The RP mode choice set comprises four modes - plane, car, coach and conventional train. The SP choice set includes the four RP modes plus a new high-speed rail alternative. Each sampled traveller provided details of their most recent intercity trip, highlighting for the access, linehaul and egress stages, the travel time components, the cost, and transfers if public transport was used.

A stated choice experiment was designed using the principles of fractional factorial design (Batsell and Louviere 1991). Three attributes each of three levels for each of the five modes were selected - access plus egress time, in-vehicle time for the main mode and total cost. This gives a total of 27 possible combinations of attribute levels within each mode, and assuming a fixed choice set, 27^5 combinations, an unwieldy number. A fraction was selected which involved treating each mode independently and creating a one-third fraction for each mode. The 9 combinations per mode were then randomly allocated to create 9 choice sets. The attribute levels were selected to be realistic variations around experience on each of the reported RP trips. The nine independent replications were administered in a random ordering, with the respondent indicating the ranking of the 5 modes on each occasion. The first-preference rank was defined as the chosen mode in the current application. We recognise the potential loss of information by constraining the response scale to a binary choice.

The empirical estimation is limited to the three attributes common across the RP and SP data plus mode-specific constants. A number of other non-design variables were evaluated such as size of the travelling party, personal income and the age of the respondent, but are not included in this empirical illustration. Three final models were obtained using FIML estimation. Unlike MNL or sequential NL, the FIML hierarchical model does not guarantee a unique global optimum. The selection of starting values for each parameter becomes crucial. A number of starting values are recommended to enable a comprehensive search over the parameter space (Hensher 1986). The MNL estimates qualify as one set of starting values. The final models are summarised in Table 1.

A comparison of the three models provides some important insights into the implications of estimating a model based on both RP and SP data. The overall fit of the combined model is better than the fit of the separate models, even after allowing for different degrees of freedom. With the exception of the access-egress time variable for the SP model, the parameter estimates for the generic attributes are comparable. The value of invehicle travel time savings varies across the models from a low of \$5.48 for the SP model and a high of \$7.29 for the RP model (in \$1986). The RP+SP model produces a value within this range. The value of out of vehicle time savings is at least 5 times the linehaul invehicle time. Although the mean parameter estimates appear reasonably stable, what has been revealed is a "distribution" of mean estimates according to the fuller variation in attribute levels and choice responses identifiable from two sources of information on traveller response. The variation in levels of service available via both the RP and the SP data provides a richer basis for predicting behavioural response.

The scaling parameter of 0.954 in this illustration is close to 1.0, suggesting that the variances associated with the unobserved RP and SP data are similar. In this instance this is an encouraging finding, suggesting that although the sources of unobserved influence on indirect utility and hence the probability of choice are not explicitly known, their variance under the SP regime is almost the same (in fact only slightly higher) to that under the RP regime.

Table 1 Empirical Comparison of Alternative Data Configurations
(estimated parameters, with t-statistics in brackets)

Explanatory Variables	**RP**	**SP**	**RP+SP**
Cost ($)	-.02849	-.03547	-.02627
	(-3.99)	(-2.08)	(-4.02)
In-vehicle	-.00346	-.00324	-.00283
time (mins.)	(-4.18)	(-1.81)	(-4.51)
Access-Egress	-.01735	.00026	-.01784
time (mins.)	(-3.96)	(.064)	(-8.49)
Mode-specific constants:			
Plane - RP	1.4413		1.6352
	(2.12)		(3.69)
Train - RP	2.0250		1.7776
	(4.91)		(5.31)
Coach - RP	.51532		0.75750
	(1.18)		(2.12)
Plane - SP		.2838	2.05508
		(0.19)	(2.69)
VFT - SP		1.9009	0.51498
		(2.73)	(1.43)
Train - SP		-.6255	0.69155
		(-1.29)	(2.28)
Coach - SP		-.8610	1.1319
		(-2.26)	(5.22)
Scale Parameter			0.954
			(1.57)
Goodness-of-fit:			
Log-likelihood at zero	-230.78	-317.06	-1039.79
Log-likelihood at convergence	-170.32	-220.06	-598.25
McFaddens rho-squared	0.164	0.306	0.425
Number of iterations	10	16	29
Number of evaluations	82	134	308
Number of observations	147	197	394
Value of invehicle time ($/hr)	7.29	5.48	6.46
Value of access/egress time ($/hr)	36.54	-	40.75
ratio of vinvt/vacceggt	5.01	-	6.31

Bradley and Daly (1991) point out that any estimated parameters in the RP+SP model which are specific to the SP data, must be re-scaled by the scale parameter before use in prediction. This applies to the mode specific constants attached to the SP branch of the hierarchical tree. This is particularly important for the mode-specific-SP constants

for modes not observed in the RP model (namely the VFT). In applying the RP+SP model, we have to decide on how to handle the mode-specific constants - we now have two constants for each mode, one reflecting the mean impact of the unobserved effects when faced with the RP situation, the other reflecting the mean impact of the unobserved effects when faced with the SP context. For prediction we could safely exclude the mode-specific SP constants associated with the existing RP modes, because the mode-specific RP constants combined with the rescaled VFT constant represent the best estimate of modal share in the presence of the VFT if all other influences on choice are not significant.

Conclusion

The integrated approach outlined in this paper provides an appealing way of utlising the richness of stated-response data while at the same time recognising that revealed preference data provide an important benchmark for predictive applications. The SP data given a depth of information which is missing in RP data, especially where applications involve alternatives which are currently not available or require the evaluation of the impact of attribute levels associated with existing alternatives which are either outside of a plausible variation centred around current experience. In one sense the unobserved heterogeneity associated with mode-specific effects which are significant but constant across the range of attribute levels to be evaluated can be explicitly accommodated via the mode-specific SP constants.

Stated response data provide a data specification which is directly comparable with RP data in that it represents realistic trade-offs within a set of attributes hypothesised to influence choice. Other stated preference methods such as univariate attitudinal questions with a satisfaction metric, while useful, are not aligned to a potential choice response. This limits their use to explanatory variables in an RP model.

As our knowledge of the benefits of a diversified data portfolio increases, we will recognise the value of incorporating SP experiments into the standard RP-oriented survey, and not treat it as a specialised once-off survey activity. This additional dimension will give the analyst a stronger set of analytical tools to assist in evaluating policy options as diverse as road pricing, alternative vehice fuels, preferences for alternative densities for urban living, and locally unavailable light rail. By evaluating these options using SP data within the context of currently revealed preferences we will give a suitable reference point for predictive outputs. As more applications and refinements occur using the combination of RP and SP data, the richness and usefulness of the approach should emerge.

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How to Make Cost-Axiomatic Pricing Work in the Real World of Transport Management

Hema de Silva
Centre for Transport Policy Analysis
Wollongong

Abstract:

Cost axiomatic pricing is a full cost recovery pricing mechanism which adheres to given cost allocation restrictions or axioms. This pricing mechanism can simultaneously accommodate most of the important objectives that are widely pursued by many public sector transport authorities in Australia, their clients, the governments overseeing these authorities and the community in general. In setting prices, a transport authority may not accommodate all objectives of these different players, it certainly may strive to find the equitable 'user-pays' type of prices that are payable by its various client groups. It is argued that such information is essential for efficient planning, investment and management of transport authorities. This paper develops a pricing methodology based on cost axiomatic allocation principles and illustrations how the information on user-pays type costs that are recoverable from different user-groups can be estimated while overcoming data problems that frequently inhibit public enterprise pricing.

Contact Author:

Dr Hema de Silva
Centre for Transport Policy Analysis
PO Box 2112
WOLLONGONG NSW 2500

Telephone: (042) 213 225 Fax: (042) 264 257