SIMULTANEOUS ANALYSIS OF CHOICE AND TRANSFER PRICE DATA

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1. INTRODUCTION

Estimation of the relative importance of components of travel disutility (or generalised cost, in its simplest form) is of fundamental importance in transportation planning, whether modelling the choices of individual travellers or assessing the value they attach to travel time or other components for evaluation purposes. The most common way in which the values of these journey attributes is estimated is through the use of choice models, in which the choice is interpreted as an observation that the traveller has preferred one combination of journey attributes to the other available combinations, i.e. that the utility of the alternative is greater than the utility of the available non-chosen alternatives.

An alternative data form that has looked attractive in principle for many years is 'transfer price' data, in which respondents are asked how much better their choice is than a specified alternative. Such data has also been called Contingent Valuation and a substantial literature exists documenting its advantages and disadvantages. The key aspect of this data which makes it attractive is that the amount of utility difference is collected, rather than, as with choice data, simply asking which alternative has the greater utility. The increased information content given by transfer price data can (in the right circumstances, which we discuss below) greatly increase the estimation accuracy and potentially help to reduce biases arising from the use of SP data.

The theoretical framework of utility maximisation used in choice modelling is also applicable to transfer price data, which raises the possibility of analysing both types of data together. In separate analysis of transfer price data, which has been used hitherto, the magnitude of the utility difference expressed by the transfer price is regressed, usually in a simple linear regression, on the explanatory time and cost variables. However, this analysis ignores the fact that we know absolutely, from the choice that is also observed, what the sign of that utility difference is. It is in principle possible to use the choice and transfer price data together, using the information on both the size and sign of the utility difference. The simplest formulation of this simultaneous estimation would imply models of the 'Tobit' type, or close relatives to that form. The key characteristic of these models is that they recognise that the traveller's unmeasured preferences – i.e., what is represented by the error term – are effectively the same, or at least highly correlated, when he or she makes as choice as when he or she responds to the transfer price question.

Further sophistication of such approaches involves extending the analysis to considering Stated Preference as well as Revealed Preference data and incorporating the correlations of the error terms in these data types with that of Transfer Price. Response biases of various types in the data, including the rounding which is characteristic of Transfer Price data, can also be included in even more sophisticated analyses.

2. UTILITY MAXIMISING FRAMEWORK

The behavioural paradigm that is currently preferred for the analysis of choices in travel analysis, as in many other fields of consumer demand study, is that of individual utility maximisation. In this framework, the traveller (consumer) is represented as choosing the alternative that maximises his or her utility. The framework has been shown to be remarkably flexible in adapting to many variants of behaviour and is at present much more complete in its development than alternative paradigms.

In some contexts, including the important example of investigations aimed at elucidating the values attached by travellers to marginal changes in the travel times they experience, it is more or less inevitable that a micro-economic framework has to be adopted to ensure consistency with the use that is subsequently made of the data.

In the 1970s, it was observed (Hensher, 1976, Daly, 1978) that the analysis of transfer price data can be set in exactly the same utility-maximising framework as is used for the analysis of choice data. Simply stated, the argument was developed as follows: a choice model represents the probability of preferring of one alternative to another by

$$\begin{aligned} \Pr\{ A \rangle B \} &= \Pr\{ U_A \geq U_B \} \\ &= \Pr\{ \beta.X_A + \varepsilon_A \geq \beta.X_B + \varepsilon_B \} \end{aligned} \tag{1}$$

making the usual approximation of the utility as a linear function of observed characteristics with ε representing the error in that approximation. Assuming specific distributional forms for ε, this equation can then be operationalised to estimate the unknown parameters β as

$$\Pr\{ A \rangle B \} = F(\beta.(X_A - X_B)) \tag{2}$$

where F is the cumulative distribution function of $(\varepsilon_B - \varepsilon_A)$.

The argument then went on: in a similar framework, one may take the transfer price to represent the utility difference between the chosen and rejected alternatives by a linear approximation

$$\begin{aligned} TP(A, B) &= \alpha + \theta . (U_A - U_B) \\ &= \alpha + \theta . \beta . (X_A - X_B) + \varepsilon \end{aligned} \tag{3}$$

using the same linear approximation as in the choice model. Clearly, it was argued, TP data can be analysed using equation (3) to obtain estimates of α and $(\theta.\beta)$, providing some simple assumption is made concerning the distribution of the error term ε. With the assumption that ε is normally distributed, standard linear regression analysis can be used to estimate the values of α and $(\theta.\beta)$. It was also noted that these estimates are also the maximum likelihood estimates under the assumption made for ε.

The problem with this analysis was first noted in this context by Gunn (1984), although much earlier work by Tobin contains essentially the same point. The assumptions being made for ε were seriously wrong.

Whilst the distribution of the maximum of two Gumbel variables is itself Gumbel, and the difference of two Normal variables is Normal, the distribution of the difference between the larger and the smaller of two Normal (or Gumbel) variables is not Normal (or Gumbel) at all. Apart from anything else, it is always positive. Gunn (1984) derives the expectation of this sort of difference from consideration of the Gumbel case: it is highly non-linear, and the distribution of the error terms is not continuous; it is truncated. A different but analogous expectation can be derived for the Normal case as is discussed later in this paper.

Gunn (1984) noted that this situation can be recognised and can be accommodated by reversing the sign of the transfer price for travellers who have been observed choosing alternative B, i.e. generalising (3) to

$$c.TP = \alpha.c + \beta.(X_A - X_B) + \varepsilon \tag{4}$$

where c is +1 if choice A is observed, –1 if choice B is observed.

The inclusion of c has the effect that the left side is positive if choice A is observed, negative if choice B is observed. Thus expressed, and assuming the sample of travellers is drawn independently of the choice made, the error term is restored to being symmetrically distributed about 0. In equation (3) the error is *not* symmetrically distributed.

Note that α could never be estimated from the evidence of the choice made, i.e. RP data. Logically, any variable which is defined by the outcome of the choice cannot affect the choice (and any estimation routine offered such a variable as part of an explanation will quickly tend to give it infinite value). That TP data (and, it turns out SP data, or repeated RP data) can estimate this extra variable is a direct result of the extra information in the these types of data, given the acceptability of the utility maximising choice paradigm.

In equations (6) and (7) of the 1984 paper, Gunn calculates the expected difference in utility given Gumbel errors (not dissimilar to Normal) as

$$EDU_C = \text{logsum} - (\beta.X_R - p_R.\text{logsum}) / p_C \tag{5}$$

(notation of the present paper) for a consumer making choice C, where R is the other choice, p gives the choice probability and

$$\text{logsum} = \log (\exp \beta.X_C + \exp \beta.X_R)$$

Because, in a binary choice situation, $p_C + p_R = 1$ and, for a logit model, $\log p_C = V_C$ – logsum, it is relatively easy to show that the utility difference can be written as

$$EDU_C = - (\log p_R) / p_C \qquad (6)$$

The positive quantity TP estimates EDU_C Thus if we estimate a model from equation (3), α is not only inertia or a feature of the questionnaire situation in which the transfer price is collected but also contains a bias which depends on the difference between the erroneous predictor $\beta.(X_C - X_R)$ and the predictor given by equation (6).

Extracting the true values of EDU and inertia from data requires an understanding of this problem; in cases where TP observations are available from respondents who have chosen each of the options in proportion to the population shares for the options, the analysis is quite straightforward, via equation (4). However, this is still not widely recognised. Probably it is for this reason, at least in part, that TP data has been little used in transport analysis in the last 20 years. This is not the case in other fields, where TP data, usually under the name of Contingent Valuation, has been widely (though not necessarily correctly) used and is only recently being challenged by figures extracted from choice modelling.

However, both choice and TP data have advantages and disadvantages and it is worth extending Gunn's (1984) work to consider a simultaneous analysis of both data types. First, however, we make some remarks concerning TP data and its use in the estimation of journey attribute values.

3. TRANSFER PRICE DATA

The initial UK experiment is described in Gunn (1981). The planning stage of a major study into Travel Time Savings in the UK had, at an early stage, identified Transfer Price as perhaps the most attractive option for collecting data. It is worth recalling the reasons, and the sequence of events which led to TP being largely ignored in transport modelling since.

In early studies (e.g. Lee and Dalvi, 1969) the method had been shown to be a measurement tool of far greater efficiency than revealed preference, in the sense that much lower standard errors were achieved for a given sample size.

This is a measure of greater information content. It seems an obvious corollary is that the TP question will be *harder to answer*, that is call for greater mental effort on the part of the respondent. If this mental effort results in a valuable and accurate assessment of the relative attractiveness of the options, it is useful information for the modeller. However, if the difficulty of the question leads to respondents providing casual, flippant or simply entirely unlikely answers, then TP will not realise its potential, and may well be much worse that SP.

In other words, it seems that Lee and Dalvi had found a good application context, and taken good advantage of it.

Whether or not TP is a useful technique for measuring journey attribute values to predict choice, or evaluate the benefits or disbenefits of an improved or worsened service, will ultimately depend on

- the **context**. Is it one where switching between options is realistic, or is choice decided more-or-less once-and-for-all at the first time of choosing, and then very hard to change (such as many mode-choice situations)? If the latter, the outcome of the cross-sectional choice (RP) will be informative about time/cost trading preferences, at least if the explanatory variables are the times and costs offered at the time the original choice was made. TP will not be, even if the time/costs have not changed. 'Other factors' would have to be taken into account, in particular the extent of the *impediments to change*.

- The **survey** itself, including all aspects of recruitment, involvement and ways and means of posing the TP question. Here, many issues come in, about whether the TP question is posed about real options or hypothetical or one of each; or indeed whether the question is asked in terms of variation of travel *time* rather than *money.* Issues of comprehensibility, credibility – ultimately, realism – also come in here

The Contingent Valuation literature gives extensive documentation of problems of this nature, see for example, Johansson (1995).

The UK study, even without the benefit of this recent research, came to a disappointing conclusion, to wit, that TP answers in the context of the most familiar travel choice context for journey attribute valuation, mode choice, could not be relied on. The reasons advanced were that
- *habit* appeared to dominate the willingness to pay of travellers for service improvements which could be gained by switching mode, or
- a way to pose the *question* had not (yet) been found to elicit sound responses, or
- both of the above.

In any event, the main survey dropped TP as a measurement tool, and the whole approach was widely regarded as untrustworthy, at least in the UK transport research community. The Gunn (1984) paper contained a re-assessment of the same data set, and came up with a rather more hopeful conclusion as indicated in Section 2 above.

4. INTEGRATING THE DATA TYPES

The situation in these models is analogous to those studied by Heckman (1979) in a paper which contributed to his Nobel prize award. In that paper, Heckman analysed the impact on regression equations of censorship or truncation based on a binary self-selection model. The key point is that a correction needs to be made to the regression to allow for the self-selection bias and Heckman gives the form of that correction. The choice between the alternatives A and B plays the role of the selection process in Heckman.

In Heckman's work the selection model is binary probit, so that the specific form of the correction (the 'inverse Mills ratio') is not appropriate for the situation studied by Gunn. That is, equation (5) or (6) is replaced in Heckman's work by a form derived from the probit choice model.

Another distinguished paper along these lines is Dubin and McFadden (1984). Following Heckman, they apply the idea of selection bias in a practical study (of choice and usage of heating systems), using a multinomial logit model for the choice process and a linear regression for the usage prediction. In their equation (24), they state the bias, for an individual who has made choice C, as:

$$D_C = (\sigma\sqrt{6}/\pi) \,.\, \{ \Sigma_R (\rho_R . p_R / (1 - p_R) . \log p_R) - \rho_C . \log p_C / (1 - p_C) \} \tag{7}$$

where p_C is the predicted probability of making choice C;

ρ_C is the correlation between the errors in the choice model and in the regression;

σ is the standard error of the conditional disturbance in the regression.

In the binary case, the values of ρ are of equal magnitude but have opposite signs (Train, 1986) and the correction can be written

$$D_C = (\sigma\rho\sqrt{6}/\pi).\{- p_R/(1-p_R).\log p_R + p_C/(1 - p_C) \log p_C - (\log p_C)/(1-p_C)\}$$

$$= - (\sigma\rho\sqrt{6}/\pi).\, \{ (p_R / p_C).\log p_R + \log p_C \}$$

$$= - (\sigma\rho\sqrt{6}/\pi).\, \{ (1 / p_C).\log p_R + \log p_C - \log p_R \}$$

(because the probabilities sum to 1)

$$= - (\sigma\rho\sqrt{6}/\pi).\, \{ (1 / p_k).\log p_{k'} + V_k - V_{k'} \} \tag{8}$$

(because this is a logit model).

Dubin and McFadden's correction for a binary case is thus equivalent to the Gunn formula, published in the same year, except for the factors:

* $(\sigma\sqrt{6}/\pi)$ which simply translates the logit-based bias into the appropriate scale for the regression model, which has an error term that is assumed to be normally distributed; and
* ρ which indicates the correlation between the regression and choice models; of course in the case of TP data ρ is 1.

Note that when the TP relates to the choice of an alternative in a multinomial case, we can form the utility of the set other than the chosen alternative and model the binary choice between the chosen and the (unknown) best alternative in that set.

If we now refer back to equation (3) we see that the expectation of ε is not 0, as is required for naïve linear regression analysis but, when α is set to 0, it is equal to the Dubin-McFadden term D_C. This is the main point made by Gunn in his paper, i.e. that when α is estimated it not only picks up any 'true' inertia, it also picks up the inevitable bias that is observed in favour of the chosen alternative when a population with varying preferences is interviewed.

To deal with this problem, Gunn recommends avoiding the self-selection problem by using equation 4; in this form, providing the data are sampled independently of choice, α can be associated unambiguously with a 'habit' or inertia (post-selection) effect. Gunn (1984) also identifies another approach as one of expressing the p's as functions of the unknown parameters, α and β, and using equation (6) together with an appropriate (truncated) error term in a non-linear regression using the Transfer Price.

The approach of Dubin-McFadden and Train follows Heckman, by instead including the term D_C explicitly in the regression and estimating the coefficient $(\sigma\rho\sqrt{6}/\pi)$, changing equation (1) to

$$c.TP = \alpha.c.D_C + \beta.(X - X_R) + \varepsilon \qquad (9)$$

where α now gives the estimate of $(\sigma\rho\sqrt{6}/\pi)$. This would appear to be a better approach than the simple one recommended by Gunn, but essentially consistent with the proposed use of equation (6), noting that $\beta.(X_A - X_B)$ and $V_A - V_B$ can be cancelled out in expectation. The advantage in this context of including the Heckman or Dubin-McFadden term in the regression is simply to reduce the error variance, i.e. to increase the accuracy of the regression.

The generalisation of separating the selection and regression models is one of the advances claimed by Heckman for his work relative to that of Tobin (1958), the third Nobel prize-winner cited in this paper. The 'tobit' model appears to exploit the sign-and-size information content of choice and transfer price data together. This model is comparatively well known and can be estimated in LIMDEP. This model has only recently been applied to transfer price data (RAND Europe, internal research) but no results have yet been published. One reason for a lack of previous published results in transport analysis might be that the tobit model is based exclusively on normally distributed error terms, which were not widely used for estimating choice models in transport analysis until comparatively recently.

The tobit model deals with regression on data which is observed only when the regressand is positive, or, in this case

$$c.TP = \beta.(X_C - X_R) + \varepsilon \qquad (10)$$

Since we know that the left side of this equation is positive, the conditions for a tobit analysis appear to hold.

An alternative approach is to use a model in the style of De Jong (1990), where the likelihood function of the choice model and the regression model are written down and the coefficients – linked or unlinked at the analyst's option – are estimated to maximise the joint likelihood over the observations. This approach requires specialised programming (e.g. in Gauss), but would give more flexibility in specifying the error term distributions.

5. PREFERENCES, HABIT, IMPEDIMENTS TO SWITCHING

The utility-maximising model of choice behaviour – see (1) – characterises the attractiveness of an option as function of measurable attributes, modified by unknown coefficients, plus a random factor which is treated as an error term, and usually attributed to lack of information on the part of the modeller. We need to be more specific in our assumptions about these random factors, and to distinguish them from effects which come into being *after* a choice has been made. At risk of over-simplification, we shall talk about *pre-disposing* factors and *post-disposing* factors, both of which are to some extent unobservable except as random variable with distributions which can be measured through experimentation.

The *pre-disposing* factors are, as discussed above, the random errors of standard choice modelling. In a binary experiment, the difference of their means can be estimated, and is usually simply called the 'Alternative Specific Constant'. Standard practice is to assume this fixed for forecasting. Models can be fitted assuming there is no qualitative difference between alternatives, and the ASC constrained to zero. (Another way of saying this is that the modeller assumes the distributions of the *pre*-disposing factors to be identical.)

Post-disposing factors are additional effects which arise after a choice has been made. For example, a choice between car and public transport may be made for the journey to work, say on taking up a new residence or new job. Subsequently, many other decisions may be made as a consequence. If public transport is chosen, season tickets can bought, familiarity with timetables and local circumstances established, routines of shopping on the way home established etc.. The net effect is that is if a transport researcher appears and asks questions such as 'By how much would the fare have to rise before you would switch to car?', he is likely to receive a very different answer to the one which underlay the time-cost trading that led to the initial decision to choose public transport.

Both answers are useful, though. If the purpose is to forecast for a non-existent future population, the results of a model with only *pre*-disposing factors is the best guide. If, however, the purpose is to predict ridership following a fare change in the near future, the second is the best guide. If it turned out that there is little difference between them, i.e. that *post*-disposing factors are trivial, this would be reassuring to know, of course. If this is not the case, the model estimation will have to take account of the post-disposing factors before eliminating them for long-term forecasting (assuming that the habit-formers have moved on to another location, if not another existence). For short-term forecasting, of course, the habit effects may well be vital!

At any rate, the existence of *post*-disposing factors, which have been variously called 'habit', 'inertia', and have been referred to above as 'impediments to change', is a plausible hypothesis. The UK team studying the value of travel time savings (VTTS) in the 1980s (MVA Consultancy *et al.*, 1987) undertook an analysis of TP data that threw up the result of finding large 'habit' effects, not as a result of a deliberate investigation but in the course of trying to use an unsophisticated model of TP to measure VTTS. They concluded that TP was not useful, and left the matter there, switching to RP and SP methods. As explained in Gunn (1984), their conclusions, as their analysis, were erroneous, as we discuss below.

6. ANALYSIS AND RE-ANALYSIS OF THE 1980'S TP DATA

The major problem with the analysis of TP in the UK 'Value of Travel Time Savings' study of the 1980's was that the statistical model was improperly specified. In this study, TP was defined constantly from the viewpoint of the chosen mode, using a model of the form

$$TP = \alpha + \beta \,.\, \Delta\text{Cost} + \gamma \,.\, \Delta\text{Time} + \varepsilon$$

with ε assumed approximately Normally distributed. γ / β was taken as 'VTTS', α was taken as a measure of 'habit'.

In fact, when the effects of selecting on the chosen mode are taken into account, the 'predictor' of TP is not the simple linear function given above, but a highly non-linear function involving p given by Gunn (1984) and given above as equation (6) in slightly different notation.

Two options were considered as a means to establish the potential existence of a 'habit' effect: one would be to use the complex predictor and a complex error term (say tobit, as suggested above) together with a 'habit' intercept, and produce a likelihood-maximising predictor of the habit effect.

Gunn (1984) chose the easy option, and dropped the self-selection information by framing the TP results as (Option A – Option B) regardless of which were chosen. This allowed the simple model to be retained, although the fact of the self-selection now meant that the habit effect took a negative sign when B was actually chosen. We now see that Gunn's approach avoids bias but, as was stated in the original paper, is not the most efficient way to handle the data. The Gunn approach would also require a minor extension (a simple weighting) if the data is not sampled independently of the choice made.

An important point to note is that the 'habit' effect that was thus measured was independent of the self-selection which can be traced back to *pre*-dispositions; it is indeed a measure of the *post*-disposition effect. It turned out to be statistically insignificant. The model, however, was extremely simple, and the analysis should also be extended to deal with enriched or stratified (e.g. choice-based) sampling, which would introduce yet another selection bias, this time imposed by the modeller.

The advance that was made here was in understanding of the effects of self-selection as it would affect TP, and the production of a device to (at least partially) avoid the complexities of the analysis that this must introduce. Meanwhile, as noted in the earlier sections, work was being done on the analyses of self-selecting data with Revealed Preference data. This work is justly famous; the next section of the paper looks at yet another aspect where self-selection can cause problems for simple analyses in the transport sector. The example is also of work on VTTS, in the latest study in the UK. The problem this time is the effect of self-selection on *stated* preference data.

7. ANALYSIS AND RE-ANALYSIS OF THE 1990'S DATA

The 1980s UK VTTS report concluded with a recommendation that a follow-up study be conducted some 10 years later, and the 1990s UK Value of Travel Time study (Accent and Hague Consulting Group, 1996) was indeed set that objective. A huge data base was assembled, dealing with many different aspects of traveller behaviour.

One of the important aspects into which the DTLR called for investigation was travellers' reactions to small time savings, and whether or not the sign (losses or gains) mattered. This aspect was considered from both the perspective of *what responses implied* for personal preferences, and from *what inferences modellers and evaluators* should draw on the 'right' values of travel time saving to use.

The data clearly showed time savings to be valued less highly than gains. Large time savings/losses were more valuable than small, per unit. A first question was why, and the study concluded that the 'sign' effects were probably due to the posing of the selected SP question (one of several which were available for this purpose) in the context of a current journey. It was argued that this was bound up with issues such as differences in long-run and short-run opportunities and penalties for journey rescheduling.

Further work (ITS and JBS, 2001) threw up the finding that, in a simple model, including a dummy in the utility function of those offered alternatives which were *identically* the same as the current journey gave a similar effect to that being attributed to the sign of the time saving/loss. This dummy variable was then included in the full model (Gunn and Burge, 2001), and proved to be highly significant there also (although the sign effects also remained significant).

Further work is currently underway within RAND Europe, and jointly with the Statistical Laboratory of the University of Cambridge, to investigate these issues. The perspective on the 'real, chosen' option as itself being the result of a previous selection process, therefore subject to self-selection bias is intriguing. The dummy variable appearing in the VTTS analysis may reflect a self-selection bias from prior processes. Possibly along with this is a 'halo' or 'habit' effect which could be affected by such considerations as the *time span* in which the respondent thought of using a time saving, or thought of making allowances for a time loss.

Crucially, with the various formulae for self-selecting bias available, and with all three of SP, RP and TP available and potentially giving joint insights greater than the sum of their separate ones, this is proving a fruitful area of research.

8. CONCLUSIONS

The discussion above indicates that in using TP data it is necessary to consider both pre-selection and post-selection biases. Both of these biases can exist in RP data but will only be identifiable if repeat observations of multiple choices are available. Both biases can be estimated from TP or standard SP data, and under certain circumstances can be identified separately.

The main theoretical conclusion of this paper is that the framework advanced by Gunn (1984) for the analysis of TP data and the identification of pre-selection and post-selection bias is consistent with the framework developed by leading U.S. researchers for the analysis of discrete choice data following self-selection. The sign-reversal procedure gives unbiased estimates whenever data is available from choosers of both options.

The additional term of equation (6) calculated by the U.S. researchers and by Gunn may add information and could be incorporated into the analysis; this would suggest the use of 'tobit' models for TP data. When data is available for only one of the options (the situation considered by the US researchers) this appears to be the only procedure available.

A serious practical observation is that the use of a current travelling situation as one of the alternatives in SP can also introduce bias into the utility of that option. This seems to have happened in the recent U.K. Value of Travel Time Savings study (see ITS *et al*., 2001, Gunn and Burge, 2001).

The main consequence of this is to underline the need to establish a better theoretical and practical state-of-the-art for SP and TP modelling.

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