

TRAVEL DEMAND MODELS FROM CENSUS DATA

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ABSTRACT: *Census data represents a resource that has considerable but unused potential in transport planning, and particularly for the development of travel demand models of the journey to work. This paper is a summary of a study in which models of mode, destination and car ownership were developed from 1976 Melbourne Census data. Models of mode and destination choice, of multinomial logit form, are reviewed, and problems associated with the use of aggregate data in models of this form discussed. The models are shown to be sensible, robust and well-performed, and clearly demonstrate the potential usefulness of the approach and the data source to transport planners.*

INTRODUCTION

The history of travel demand modelling in Australia is a chequered one, characterised more by continued (and expensive) failures than by notable successes. Of the various modelling exercises undertaken as part of the transport studies in the major Australian cities, only the Perth 2000 study provides an exception to the rule that the end result is frustration, alienation, and widespread disenchantment with modelling and modellers. One consequence is that many cities are without robust (often, even rudimentary) techniques for assessing the transport implications of various policy changes or transport investment. Bad experiences plus the high cost of data collection mean that transport planning agencies are usually unwilling to rectify the situation; existing models are seldom updated using new data, and faulty models are seldom re-estimated.

The general absence of models that could be used for even broad brush testing of transport policy options for Melbourne, and the unavailability of adequate data on which models might be estimated, prompted an investigation of the potential of Census data for this purpose. It was found that the form of the data available from the 1976 Census appeared to be capable of supporting the development of models of mode and destination choice for the journey to work, and of car availability.

It was considered that such models could be used in a sketch planning context to give useful information about the direction and magnitude of changes resulting from transport policy actions. Further, models based on Census data can be regularly updated as new data becomes available, and the data is almost costless. Finally, the data is uniformly available for all Australian cities. This means both that experiences in one area will be largely transferable to others, and -on a more academic but no less useful note - questions of model transferability can be examined more rigorously than has previously been possible.

The benefits of using this data source for model development are therefore potentially major, and a study of the problems associated with its use is nearing completion. This paper presents an overview of the models that have been developed, the problems encountered, and the theoretical insights that have been gained. For reasons of space, only mode and destination choice models are discussed.

DATA FOR MODEL DEVELOPMENTCensus Data

The data used in the study was from the 1976 Census, when for the first time an LGA-level cross classification of data was made available. This was Table Generator Matrix 17, which is a matrix of all usually-employed persons in the Census, defined on the dimensions:

origin	55 Melbourne LGA level
destination	" " "
industry	13 ABS summary codes
occupation	11 ABS " "
mode of travel to work ⁽¹⁾	30 mode combinations

1. The trip to work as such is not recorded in the Census, but inferred for usually-employed persons from residential and employment addresses.

income	7 categories
vehicle availability	7 categories
age	7 categories; 15-65+
sex	2 categories

While the data is physically ordered as a record for each individual, with membership of each category recorded as a code number, there is associated with each observation a weighting factor. This is used to expand the actual recorded observations to the total recorded in the Census, and is necessary because only approximately half the original data available was coded.

Because of the form of the data, the option exists to deal either with individual records sampled from the base data, or with the weighted totals. The latter option was chosen, because representativeness of the model results would be thereby ensured. Repeated sampling and estimation would be necessary with the former option, to ensure that model representativeness had been obtained. Other difficulties exist that make it more attractive to deal directly with the aggregate data.

Other Data

Level-of-service (LOS) data necessary was obtained from highway and public transport networks (see Acknowledgements). These existed for (approximately) 1976 at a 708 zone level. They were converted to an LGA level by simply selecting a zone to "represent" an LGA. No more refined approach was warranted, as no trip-table existed at this level to be used for weighting in any averaging procedure.

Unfortunately, the public transport LOS data could not be acquired for the individual modes train, tram or bus, so only a composite "public transport" mode could be defined. This somewhat limits the usefulness of the resultant models, but will not affect the demonstration of the usefulness of the data, or the validity of the approach taken.

MODEL FORM

The form of the models used throughout is the multinomial logit (MNL) model. It is now well known that if the axiom of utility maximising choice behaviour is accepted, the MNL model is one of a family of models that alone can replicate the linkages between interdependent choices faced by an individual. This is one of its most important attributes in the modelling of travel demand, and one which significantly contributes to the conceptual and theoretical appeal of the model form. In application, it may not always have been as successful as its adherents would have liked. In general, however, failures have not been due to the model form, but to inadequate data collection and processing (shortcomings that no modelling technique worth using can overcome), inadequate understanding of the contextual or theoretical bases of the model, or overly high expectations of what models of any type can provide.

The MNL model is best known for its use with individual "disaggregate" data, but it can be used with aggregate data of the type available from the Census. There are two significant differences between the use of the two data types in an MNL model. The first is that, with individual data only a 0/1 choice probability is observed, whereas with aggregate data, group choice probabilities are observed. This marginally

affects the estimation procedure; its practical implication is that standard logit estimation procedures (ULOGIT, BLOGIT, SLOGIT, etc) cannot be used. The second is that the theory on which the model form is based is that of individual choice. The use of aggregate data in model estimation may give rise to considerable biases in prediction, and special care must be exercised to avoid this problem.

Model Theory

Space does not permit a full development of the theoretical and statistical foundations of the MNL model, and it is necessary to assume that the reader is familiar with these. However, model theory and its practical application should not be separated (to such separation can be attributed many of the previously referenced "difficulties" experienced with travel demand models). Further, it is recognised that those to whom this paper may be of most use - planners looking for a robust and well performed modelling approach based on readily accessible and revised data - may not be as conversant with the theory as those of more academic inclinations. Therefore, a summary of some of the more important but often overlooked aspects of the model theory is given below

The generally-known form of the MNL model is

$$P_j = \exp V_j / \sum_{j \in A} \exp V_j \quad (1)$$

where P_j = probability of choosing alternative j from a set of A available alternatives,

V_j = the observable utility function describing the alternative and characteristics of the individual or group = $\sum_k \beta_k X_{jk}$

where X_{jk} = k th characteristic of the j th alternative

β_k = coefficients to be estimated.

However, the model form and its underlying theory derive from the assumption that V_j is only the observable component of a more general relationship describing the utility of an alternative,

$$U_j = V_j + \epsilon_j$$

where ϵ_j is a random, component of unobservable attributes, and has a probability distribution. The distribution that gives rise to the MNL model is the Extreme Value Type 1 (Gumbel) (not Weibull) distribution. This has a variance that must be assumed constant across alternatives for the MNL model to be derived, and a mean that must, again necessarily, be equal to zero, but can only be if the term V_j includes a constant term. The model form that derives from these assumptions may more rigorously be written as

$$P_j = \exp(\lambda V_j) / \sum_{j \in J} \exp(\lambda V_j) \quad (2)$$

where λ is the parameter characterising the constant variance of the distribution, $\text{Var } \epsilon_j = \pi^2/6\lambda^2$.

In the model (2) above, the parameter λ cannot be separately estimated.

Reference will be made later, to the properties of and assumptions underlying this model, in discussing models of destination choice.

Model Estimation

The parameters β_k are estimated by maximum likelihood estimation. Existing logit estimation programs are designed for use with individual data, which gives a marginally different likelihood function from that deriving from group data. An estimation program was developed for this application, and is based around the FMFP function minimisation subroutine available in the SSP library of subroutines. A user-coded program to evaluate the function and its first and second derivatives is required. The function minimised is minus the log of the likelihood function; for data of the form used in this study, the relevant functions are given as:

$$\text{Likelihood function, } L = \prod_o \prod_m P_m^{T_m}$$

$$\text{Loglikelihood function } L^* = \sum_o \sum_m T_m \ln P_m$$

$$\text{where } P_m = \exp(V_m) / \sum_m \exp(V_m)$$

T_m = number of observed choices of alternative m in any group observation, o .

The Aggregation Problem

A familiar problem with the application of models estimated using individual data, to population groups for which only group averages of utility function variables are available, is that of "aggregation bias". This arises because group choice probabilities calculated using group average variable values are not the same as the sum of the individual choice probabilities for all members of the group. This problem is more fully discussed elsewhere (Koppelman, 1975; McFadden and Reid, 1975; Reid, 1978), but arises in part because of heterogeneity in response across different socio-economic or other groups. One way to practically reduce this error, and retain the efficiency of working with aggregate data, is to develop the relevant models for particular population groups ("market segments") known to be relatively homogeneous in their choice behaviour.

A similar problem exists with the use of aggregate data in model estimation, and a similar solution may be used. In this context, the problem is that a model estimated for one group with a particular distribution of socio-economic characteristics cannot be applied without error for the estimation of the choice probability of a group with a different distribution. Again, the appropriate strategy is to use market segments for model estimation and subsequent application. As will be seen, this also has the effect of increasing (often substantially) model predictive performance.

A more subtle problem with the use of aggregate data exists, for which no solution has yet been found. This problem arises from the fact that grouped data has a mean and a variance. It is necessary to assume that the variance of the utility function (or the variance of the random or unobserved components of the utility function) is constant for all alternatives. When an alternative is described by an average value for a variable (travel time, alternative-specific socio-economic variables, etc), that itself has an unobserved variance, this assumption will no longer apply. This violation is a potential source of error, but space does not permit further exploration of the problem. It will be later referenced in the discussion of destination choice models.

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MODAL CHOICE MODEL

Modal Alternatives

The network data and the modes used as reported in the Census limit the definable alternatives to:

car driver
car passenger
public transport

While there were 28 categories of responses to "mode of travel to work" in the data, including multiple modes, responses giving multiple modes could not be used because of imprecise framing of the question. Multiple mode use was not a requested response, and consequently many such trips would not have been reported. Categories were collapsed, by inspection, to the three above. Observations reporting *taxi, m/cycle, bicycle, walked, worked at home and not stated* were excluded from the data set. Intrazonal travel was excluded throughout.

Market Segmentation

Model performance can be substantially improved if observations are separated into groups of more homogeneous response with respect to mode choice, and separate models developed for each group. Possible segmenting variables that are likely to give rise to substantial between-group variance are

occupation
car availability
CBD travellers.

All were used, and results are reported later in this section.

Variable Form and Definition

The aggregate nature of the data makes the form in which variables are defined less obvious than usual. The variables that might enter the various utility functions in some form, that are available from the Census data, are *age, sex, income and car availability*, with the latter variable being potentially useful as a segmenting variable also. Because the data is cross-classified, variables can be included either independently or interactively with other variables. They may be discrete, or continuous if average values are used.

Consider the two variables age and income both of which affect mode usage, and for each of which there are 7 membership categories. Each could be specified as

- a) a weighted average value for the observation (the group of travellers for an origin-destination pair, T_{ij});
- b) as up to 7 independent variables for each in the utility functions for each of 2 modes, of the form $T_{ija(l)}/T_{ij}$, where l denotes the particular age or income category;
- c) in combination as up to 49 variables in 2 utility functions, giving the interaction effects of age and income.

For practical model estimation, a much more limited set of variables is necessary, and interaction effects, interesting though they may be, cannot

sensibly be included. Approach b) was used, but only 1 category used for each variable. This was determined from inspection of cross-tabulations of mode used by the relevant variable. The category or set of categories that appeared to have the greatest influence was used; the resultant variables are listed below.

Sex: % of females in T_{ij}
Income: % of T_{ij} with income < 6000 p.a.
Age: % of T_{ij} in age group 20 +
Cars available: where used, as a weighted average of cars available.

Other variables used are level of service and fares.

HWT: highway travel time from the network; no terminal times added;
PTT: public transport travel time, plus half access time; derived after considerable testing of a variety of specifications;
FARE: Public transport fares, based on a distance schedule, and using highway distances.

Various other variables from the LGA summary file and other sources were tested; these include

TEND: a measure of trip end density;
SEPH: % of separate households in an LGA;
LTOD: % of LGA licensed to drive;
IUD: an inner urban dummy.

RESULTS OF MODEL ESTIMATION

A description of each model developed is unnecessary, and only the major conclusions are presented.

Effects of Market Segmentation

By Car Availability

Models for the two segment, zero cars available and 1+ cars available, were developed separately, with only car passenger and public transport modes available to the first. To test whether segmentation improves predictive performance, the combined models were compared with a third estimated without segmentation, but including a zero car household dummy. The measure of comparison chosen is the very simple one of the sum of absolute residuals over all observations, for each mode, $\sum |T_{om} - \hat{T}_{om}|$. The comparison is reported below. It should be noted that the various models were estimated on approximately half the data set (every second valid observation), while the residuals were calculated by applying the estimated models to the whole data set.

	Total Trips	Residuals From:	
		Combined segmented models	Unsegmented model
Public Transport	168284	36168	39219
Car Passenger	73857	16323	16394
Car Driver	420985	35516	39877

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It can be seen that performance is improved by segmentation, but the difference is not as great as might be expected, largely because the number of zero car households is small, and the dummy variable used in the unsegmented model accounts for a large amount of the effect.

By Occupation Group

The 11 Census occupation groups were collapsed into 3 on the basis of similarity in observed trip lengths and type of occupation. (Brown, 1982). The resultant groupings could be generally described as *professional/administrative*, *sales/clerical*, and *blue collar*. Models were estimated for each separately, but segmentation by car availability was not carried through for this exercise (6 models would have resulted). Model performance was compared on the same basis as above, and is reported below.

	Residuals from: Occupation segmented models	Unsegmented model
Public Transport	35698	39219
Car Passenger	14940	16394
Car Driver	34902	39877

A substantial improvement in predictive performance is obtained from segmentation by occupation group. Perhaps surprisingly, this segmenting dimension appears to perform better than car availability. This is surprising because car availability would appear to be a more direct situational constraint on choice than occupation. However, the variable is not really an adequate measure of availability, in that it does not include any of the important influences of household competition for available vehicles. Without this effect, it must be questioned whether the measure is really one of "availability" at all. Segmentation by occupation, on the other hand, appears to give a better discrimination between socio-economic groupings with different usage patterns, and takes better account of the interactance effects of characteristics of sex, age, income and car availability. These interactance effects are evident in the results (not reported), but cannot be made explicit by the forms of the variables and the utility functions used. In the absence of such a specification, segmentation by occupation provides a useful proxy for their inclusion.

By CBD/Non CBD Travel

An inner urban dummy variable used in the previous models to flag trips to these areas was highly significant, indicating differential choice influences on trips of these types. This points to the need to develop separate models for the two types of trips. This was done, and the results of this segmentation reported below.

	Total Trips	Residuals from: CBD/Non CBD Segmented Models	Unsegmented model
Public Transport	168284	28776	39219
Car Passenger	73857	15314	16394
Car Driver	420985	28129	39857

As expected, segmentation by CBD/Non CBD destination gives a major improvement in model performance over the unsegmented model, and over occupation-segmented models. While predictive performance for the car passenger mode is slightly worse than that for occupation group models, public transport and car driver prediction has improved by 26% and 28% over the unsegmented model, and each by 19% over the occupation group models. Further improvement would be achieved by carrying through occupation segmentation though this has not been undertaken, as the power of the segmentation approaches has been clearly established.

Results of Model Estimation

The detailed results of the CBD/Non CBD mode choice models are given below.

Variable	Utility Function	CBD Model		Non CBD Model	
		Parameter	t-stat	Parameter	t-stat
HWTT	Car Driver	-5.40	-33.5	-5.48	-42.0
CARAV		.48	5.2	.266	6.8
LICTOD		-.026	-8.8	.012	9.6
INC		-.023	-7.9	-.014	-12.5
AGE		.014	4.0	.018	11.6
HWTT	Car Passenger	-5.78	-30.4	-5.89	-40.0
OCARS		1.67	6.4	.634	4.7
SEX		-.011	-4.1	-.001	-1.1
TENDENS		-.0002	-0.8	.003	8.6
CONST		-.72	-1.6	.54	3.0
PTTT	Public Transport	-2.35	-20.1	-1.72	-25.0
PTFARE		-1.90	-15.0	-2.32	-18.0
OCARS		5.0	-23.3	6.13	55.0
SEX		-0.02	-9.6	.011	15.7
INC		-0.003	-1.7	-.006	-5.0
CONST		1.36	3.0	.90	4.8

Overall Performance

The performance of the two models, in terms of their predictive ability, is good. Based on the results reported previously, the total % error for each mode is:

Public transport	17%
Car passenger	21%
Car driver	7%

These are low, and would be reduced further if segmentation by occupation group were used. It should be noted that the non-CBD model was estimated on only approximately half the data set; these results are from the models applied over the full data set.

Variable Performance

The first observation that must be made relates to the often extremely high value of the reported t-statistics. These are high basically because aggregate data for approximately half the total workforce is used in the model. Variables significantly influencing behaviour will in this situation be highly significant.

The coefficients of the level of service variables (in minutes/100 and \$ for PTFARE), are with the exception of PTTT, of expected order of magnitude. A previous mode choice model for the choice of car vs. train for the Melbourne CBD work trip gave values for IVTT(Car) and PTFARE of -4.5 and -3.1 respectively (Brown, 1977). Given the incomparability between the data sets used in each study, the relative constancy of these parameters indicates that the models reported here are reliable.

The low value of the coefficient for PTTT reflects difficulties experienced in defining the magnitude of this variable. Public transport network in vehicle time, plus half the zonal access time, was eventually used

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This was selected after considerable experimentation, on the basis of predictive performance. It is apparent that for an operative model to be developed, at least the access time component needs to be revised.

The car availability measures clearly indicate that segmentation on zero car availability will improve model performance, as previously indicated. However, this would be impractically cumbersome when coupled with occupation and CBD segmentation, requiring 12 separate models. The influence is reasonably well included through a dummy variable as above.

Of the socio-economic variables, two give anomalous results. The LICTOD variable, measuring % licensed to drive in an LGA, has a surprising -ve sign, in the CBD model. As well, SEX (% of females) takes a negative sign, in contrast to previous models where it was consistently positive. It would appear that these results are due to interaction effects in the data, and need further exploration.

Conclusions

The models reported perform well, and with some inconsistencies give plausible, highly significant coefficient estimates that accord with previous experience. Other models developed but unreported are more consistent, but do not perform quite as well. Further development will iron out these minor deficiencies.

The strong conclusion that may be made is that the data source has been shown to be capable of producing robust, sensible and relatively well-behaved and highly performed models of mode choice. While there are development costs, these are orders of magnitude less than those associated with models based on special-purpose data sets. The data is freely and widely available, and can be used for the development of sketch-planning models that should be of considerable use to transport planning agencies.

DESTINATION CHOICE MODEL

Data reporting residential and workplace location is almost all that is required for spatial interaction modelling. For worktrip destination choice modelling, only a trip table and some measure of zonal separation are necessary. Previous work (Brown, 1982) has reported the use of Census data in the development of singly constrained gravity models of trip distribution. Using aggregate data, the singly constrained gravity model appears to be identical to an MNL model of destination choice. This model form is, however, theoretically incorrect in this context.

The Need For a Doubly Constrained Form

The conventional singly constrained gravity model (SCGM) is identical to an MNL form that does not contain an alternative (destination) specific constant. The utility function describing destination attractiveness for each alternative should include variables measuring this. For the worktrip, there is little understanding of what actually constitutes "attractiveness" - other than the attraction variable of total employment. This is not a measure of utility, but a way of aggregating individual trips from all origins to a destination, over all opportunities at the destination. Consequently, separate measures of attractiveness as such are never included in worktrip destination choice models. Because each destination alternative is quite different in its inherent but unmeasured attractiveness, there is no reason to suppose that the distribution of the random component of utility - accounting as it does for unspecified components of utility - will be identically located for all alternatives.

However, any MNL model that does not include an alternative specific constant (ASC) implicitly requires that such alternative-specific influences are identical. This is obviously incorrect in this context, and an ASC that proxies for the differential effects of destination attractiveness is necessary.

The theoretically and practically required inclusion of an ASC in the destination choice model makes the MNL model identical to the doubly constrained gravity model (DCGM) (Cochrane, 1975; Williams, 1977; Daly, 1982).

If origin-zone-specific (OZS) parameters are estimated for a SCGM, these will exhibit marked map-specificity (Brown, 1982). The practical implication of this is that the model is locked into the zone system in which it was estimated, and for prediction can only be used in this system. This is an unacceptable constraint for any model that is required to be generally applicable, as most travel demand models should. However, the use of a model that includes an ASC in the utility function for J-1 destinations almost completely removes this effect, as demonstrated below.

A Doubly Constrained MNL Destination Choice Model

The data used is in the form of a trip table, the cells of which constitute the observations for model estimation. Because by definition the table is "in balance" (row totals = zonal productions, column totals = zonal attractions), the model must preserve this relationship in its estimated results. It is well known that market shares are preserved by the use of an alternative specific constant in all but one of the utility functions. It has previously been stated that there is a theoretical requirement for this. The doubly constrained MNL model is no more than this conventional model. It may in the context of destination choice be written as

$$P_{ij} = \frac{A_j e^{V_{ij}}}{\sum_j A_j e^{V_{ij}}} \quad (3)$$

where P_{ij} = probability of travelling from i to j

$V_{ij} = C_{ij} + b_j$

C_{ij} = some measure of travel cost, taken as travel time or distance

A_j = zonal attractions, excluded from the utility function as it is not a measure of utility, but an aggregation measure only

β = impedance parameter to be estimated

$b_j, j = 1 \dots J-1$, is the ASC referenced.

To examine the extent to which map-specificity of OZS parameters is removed by the use of a DCGM, a two stage estimation procedure was used. This is necessary because it is not easily possible to estimate a single set of 54 attractiveness parameters (ASC's) as well as a set of 55 OZS parameters. Firstly, a single set of 54 ASC's were estimated using model (3). The estimated b_j were then included as constants in the utility function of an origin zone specific model, from which β_j was estimated for each origin separately. These approximate β_j are plotted in Fig. 2, and may be compared with the OZS parameters from the singly constrained model, plotted in Fig. 1.

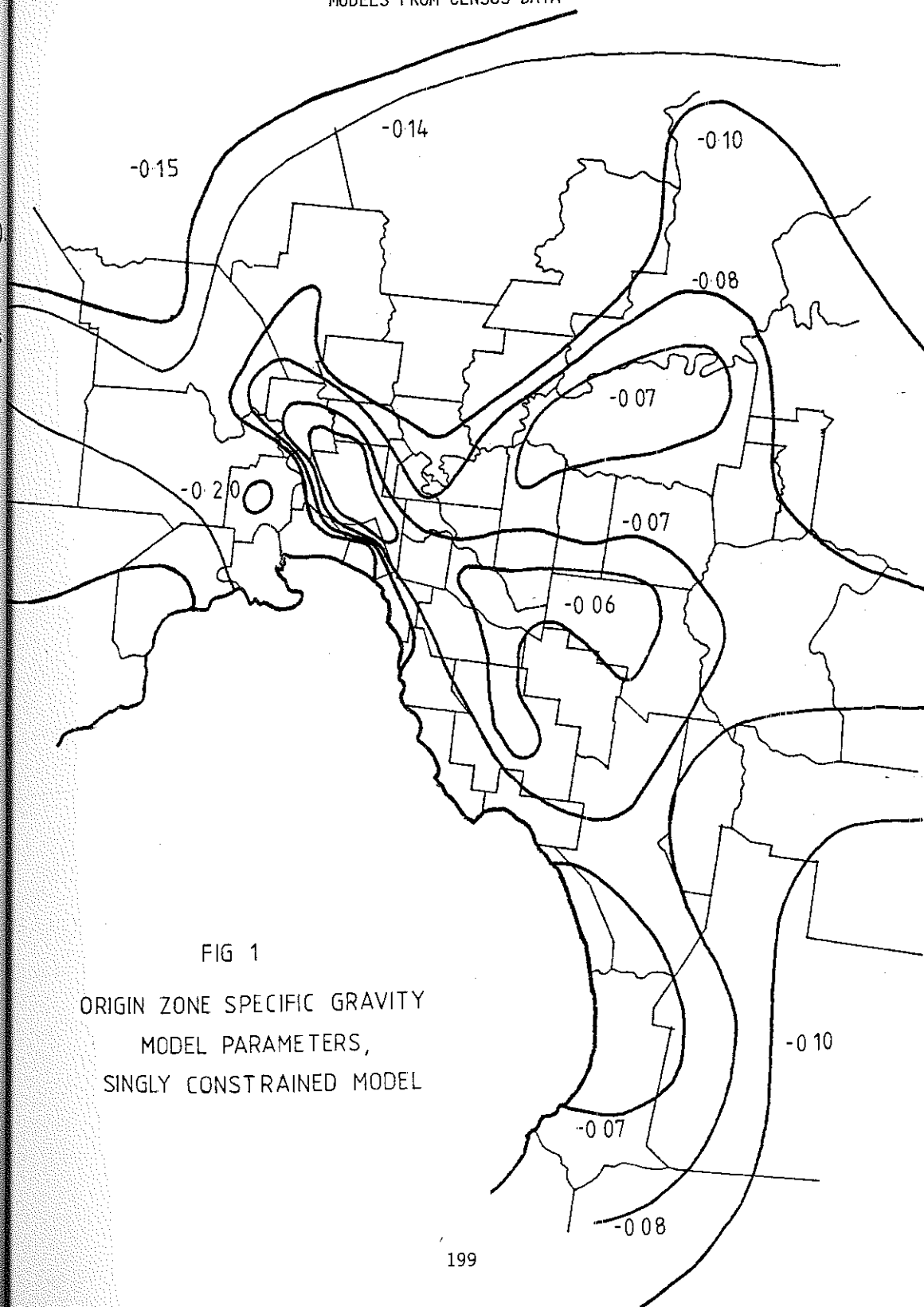


FIG 1
ORIGIN ZONE SPECIFIC GRAVITY
MODEL PARAMETERS,
SINGLY CONSTRAINED MODEL

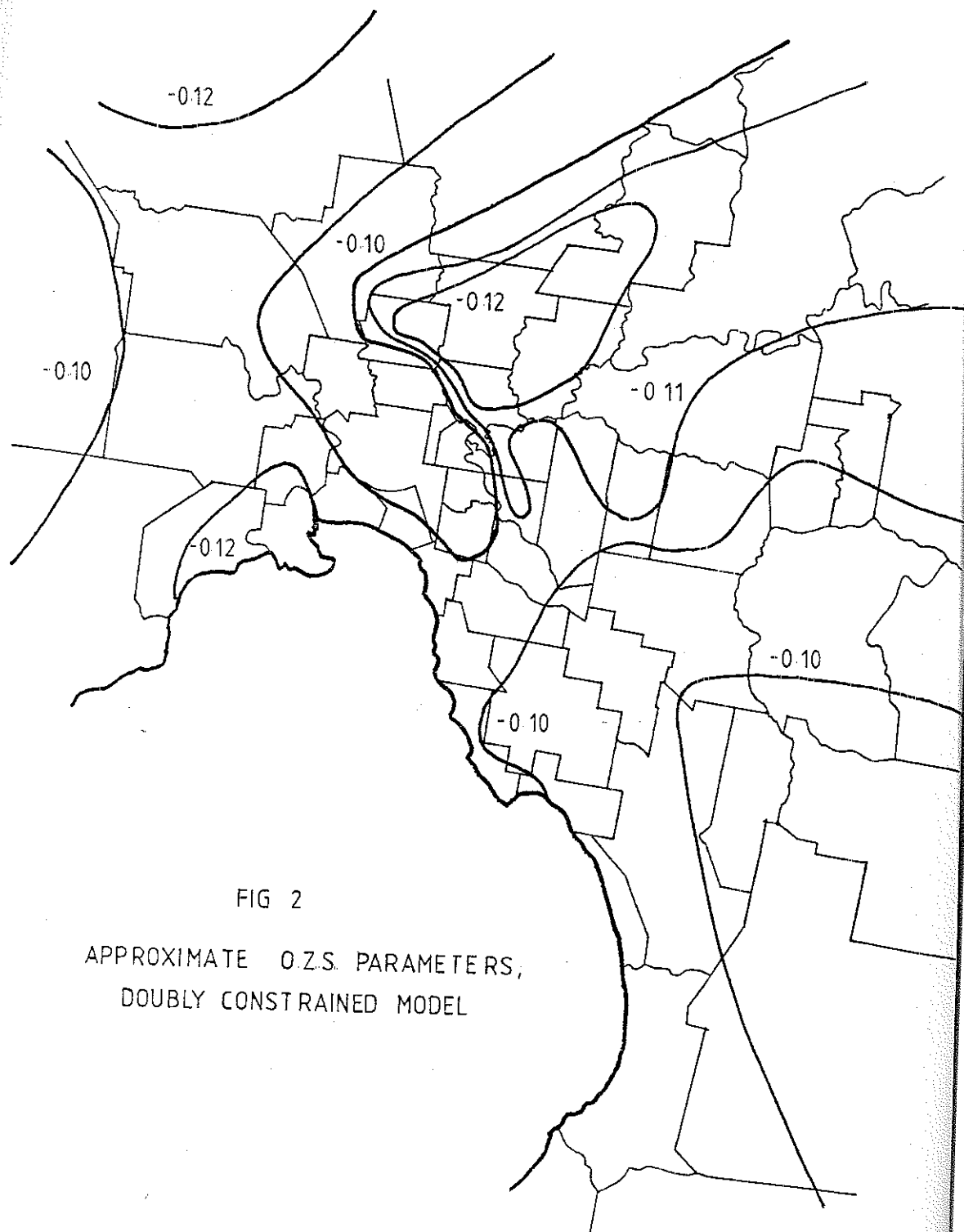


FIG 2
APPROXIMATE O.Z.S. PARAMETERS,
DOUBLY CONSTRAINED MODEL

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Quite clearly, what may be termed the *structural dependency* of the singly constrained model has been removed.

The doubly-constrained form also explains more of the variation in the data on which it was estimated. Using as a simple measure of performance the sum of absolute residuals over all observations, the following models may be compared.

	Sum of Residuals $\sum_{ij} \bar{t}_{ij} - \hat{t}_{ij} $
Single parameter SCGM	280,798
OZS SCGM	252,228
Doubly constrained model	222,300
Total number of non-zero cells	2,708
Total trips	706,151

Predictive Performance on a Different Spatial System

While model performance in estimation is indicative of at least relative performance in prediction, the latter is really the acid test. Because a model of the type discussed can sensibly only be estimated using all non-zero cells in the matrix, the use of a hold-out sample for prediction is precluded. Interest should be directed at model performance in prediction on a different spatial scheme than that used for estimation, and for this analysis a 35-zone system was created by aggregating selected zones from the full 55-zone scheme. A new trip-table and travel time matrix for this system were created, and a new model estimated as a yardstick against which predictive performance may be compared.

It is in this situation that the aggregation problem previously referenced assumes some significance. Average travel times between LGA's were constructed from a lower level (708) zonal system. Hence there exists also an interzonal travel time variance, and the variance of the utility function will not therefore be constant across alternatives. This is demonstrated below.

The utility function for the destination choice model is written as

$$V_{ij} = \beta C_{ij} + b_j + \epsilon_{ij} \quad (4)$$

where the terms are as previously defined, and ϵ_{ij} is assumed to have constant variance. However, C_{ij} is replaced in practice by \bar{C}_{ij} , and

$$V_{ij} = \beta \bar{C}_{ij} + b_j + \epsilon_{ij}^* \quad (5)$$

It is easily seen that $\text{Var } \epsilon_{ij}^*$ is not constant over alternatives, as \bar{C}_{ij} has a variance that is different for each ij pair.

Write

$$V_{ij} = \beta C_{ij} + \beta(\bar{C}_{ij} - C_{ij}) + b_j + \epsilon_{ij} \quad (6)$$

Then

$$\text{Var } V_{ij} = \beta^2 \text{Var } C_{ij} + \text{Var } \epsilon_{ij} \quad (7)$$

$$= \text{Var } \epsilon_{ij}^*, \text{ from (5)}$$

Hence $\text{Var } \epsilon_{ij}^*$ is not constant, and the underlying assumptions of the model are violated.

An attempt was made to correct for this problem, but was partly unsuccessful, and cannot be discussed further. The potential consequences (which apply to all MNL models that use zonal average travel times) are that the β parameter will be biased in some way by the aggregation scheme within which it is estimated. Application in a different aggregation scheme would then lead to significant errors. This was not experienced in the application, as discussed below.

Because both the singly-constrained, origin zone specific model, and the doubly-constrained model include parameters specific to individual zones, application in another system requires averaging of parameters over the aggregated zones. Both simple averaging, and weighted averaging using zone productions and attractions as weights for the OZS parameters and the attractiveness parameters respectively, were used. Simple averaging was found to be satisfactory.

The predictive performance of each model is given below, compared with that of the model estimated on the new scheme. The performance of the latter model forms the lower bound to obtainable predictive performance.

	Sum of Residuals $\sum_{ij} T_{ij} - \hat{T}_{ij} $
Doubly constrained model estimated on 35-zone scheme	144,058
OZS model in prediction	317,306
Doubly constrained model in prediction	145,821
Total non-zero cells	1,082
Total trips	641,161

These results dramatically demonstrate the validity of the hypothesis that the singly constrained model is entirely dependent on the spatial scheme in which it is estimated, and cannot usefully be applied outside that context. On the other hand, it is also clear that the doubly constrained model is not dependent on the spatial scheme (at least, in the same way), and when applied in a different scheme can perform extremely well.

By comparing the residuals from the model estimated on the 35-zone scheme with those from application of the model estimated at the 55-zone level to the new aggregation scheme, an upper limit to the error attributable to "aggregation bias" is obtained. It can be seen that this difference is minimal, and gives some confidence that what is a theoretical concern may not be of practical significance.

A caveat must be sounded, however, as regarding temporal rather than spatial transferability of a model of this type. The attractiveness parameters estimated will obviously be dependent on structural relationships that will change significantly over time, but in some unknown way. Their use in predicting future-year interchanges is likely to be significantly inferior to the performance reported above. One solution to this problem that may be useful in using Census data for model development and subsequent application, is to estimate (short-term) horizon year parameters from the

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parameters estimated for previous Census years. For instance, model application for 1984 could be based on parameters obtained from the extrapolation of 1976 and 1981 estimated parameters.

Model Application in Practice

Some aspects of the way in which the model was estimated deserve summary discussion, as they affect the application of the model in forecasting. A further discussion is given elsewhere (Brown, 1982).

The first has been mentioned above; attractiveness parameters for forecasting may be obtained by updating parameters estimated for previous periods.

The second concerns the fact that the models have been estimated using only non-zero cells in the matrix. For application, however, it is not possible to predict where zero cells will occur, and the model will predict interchanges in all cells defined by the zoning system, unless external constraints are imposed. One possible constraint requires the definition of a threshold trip length, beyond which zero interchanges are supposed. Only cells which have travel times which are less than the threshold will contain predicted interchanges. The model is estimated on all cells within this threshold, and similarly applied in the horizon year. Zero cells are increased by 1 for estimation.

Finally, the models reported have been estimated on data excluding intrazonals. It was found that inclusion of intrazonals both significantly altered parameter estimates, and significantly reduced the model's ability to predict interzonal interchanges. A two stage procedure in forecasting is necessary with this approach, and intrazonals are separately predicted by the simple expedient of factoring up base year intrazonals using the previous Census period intrazonals. This is identical to the approach suggested for obtaining horizon-year attractiveness parameters, and has been found to give markedly superior performance over a model that includes intrazonals (Brown, 1982).

LINKING MODE AND DESTINATION CHOICE MODELS

The theoretical appeal of the MNL modelling framework is that it follows directly from theories of individual choice (utility maximising) behaviour. Its major practical appeal is that this theoretical base allows for the modelling of interdependent choices, and provides a test for the validity of the assumed sequence of choices. Mode and destination choices are interdependent, in that changes in the travel environment affecting mode choices will also affect destination choice. It is generally assumed that mode choice for the work trip is made conditional on destination choice. Their interdependence is effected through the use of a variable in the destination choice model that reflects the total utility to each destination available from all modes. A substantial literature related to the derivation and interpretation of this variable exists (Domencich and McFadden, 1975; Williams, 1977; McFadden, 1979). This variable, variously referred to as "inclusive value", "composite utility" or "logsum", is simply the natural logarithm of the denominator of the mode choice model. Its parameter is theoretically constrained to the range 0 - 1, and its value reflects the level of choice interdependency that exists. (For a fuller discussion, see Hensher and Johnson, 1981, Ch. 4).

The inclusive value variable has the effect of allowing the impedance function to be independent of chosen mode. In the previous destination choice model, the travel time variable used was highway travel time, irrespective of the distribution of modes used. However, the inclusive value is the only theoretically correct way of combining travel time (or generalised cost) by various modes into a composite measure that can be used for all groups (see, e.g., Williams and Senior, 1977).

As will be shown, usual practical approaches to the linking of mode and destination choice models appear to be incorrect, and a solution to this problem is suggested and, in part, tested empirically.

The Destination Choice Model and the Conventional Mode Choice Inclusive Value

To explore the level of interdependency between the mode and destination choice models, and the improvement in performance of the latter when this is allowed for, the destination choice model with the addition of the inclusive value or logsum from the mode choice model, was re-estimated.

Because the logsum is a measure of composite cost, it is not usual to include other measures of separation in the utility function of the destination choice model. However, it is argued here that separation has dual but somewhat distinct influences; it affects the cost of travel that is traded against the trip-end benefit, and as well reduces perception of the availability of opportunities at distant destinations. Distance is the appropriate variable to capture this latter effect (if possible at all), and is less strongly correlated with composite cost (in the logsum term) than is some measure of travel time. To explore the possibility of capturing both effects, distance is also included in the utility function.

The models estimated were of the form

$$P_{ij} = \frac{A_j \exp V_{ij}}{\sum_j A_j \exp V_{ij}}$$

where (1) $V_{ij} = \beta C_{ij} + b_j$

(2) $V_{ij} = \theta IV_{ij} + b_j$

(3) $V_{ij} = \beta D_{ij} + \theta IV_{ij} + b_j$

In (1), C_{ij} is highway travel time. In (3), D_{ij} is highway distance. The results are given below; the ASC's (b_j 's) are not included.

	Parameter estimates		Residuals
	β	θ	$\sum_{ij} T_{ij} - \hat{T}_{ij} $
Model 1, with C_{ij}	-0.099	-	222,300
Model 1, with D_{ij}	-0.134	-	227,139
Model 2	-	1.658	284,536
Model 3	-0.116	0.274	227,322

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It is apparent that the model based on the logsum variable by itself is completely inadequate, both in terms of performance, and because the parameter value lies outside the range in which it is theoretically required to fall. While Model 3 gives plausible results, with an acceptable parameter value, the fact that model performance has not improved, and that the parameter value is lower than expected, gives rise to concern about the nature of the inclusive value variable, and its role in linking mode and destination choice models.

Some Observations on the Nature of the Inclusive Value Variable

A detailed investigation into the problem revealed that in many situations, the socio-economic (SE) variables in the mode choice model contributed more (positively) to total utility than was contributed (negatively) by the level of service variables. The effect of this is to give a high utility to origin-destination pairs at large distances and with few interchanges. As there is no consistency in this effect, it has the result of making most of the values of the IV variable, and the DC model, spurious.

It is obvious, on reflection, that to the extent that socio-economic variables reflect only habit or captivity patterns, they have no place in the inclusive value term, which is really simply a measure of the composite costs of travel over all modes between an origin-destination pair. However, it is always tempting to include in a mode choice model as many variables as is possible, to try and capture (in a largely non-behavioural way) as much of the observed choice pattern as possible. As Williams and Senior (1977), the only other authors found to have recognized this problem, have noted, the most appropriate strategy is to segment the data so that socio-economic variables do not compete directly with level-of-service variables in the model. However, there are many SE variables that frequently contribute significantly to mode choice models for which this strategy is inappropriate. Further, the complexity of the segmentation scheme necessary to fully account for important SE influences makes this approach impossibly unwieldy if all influences are to be included.

Nevertheless, it is clear that only level-of-service variables, and not socio-economic influences that reflect only constraining effects, should appear in the utility functions used to construct the IV variable. Only segmentation can properly capture important differential socio-economic influences on choice and at the same time allow the IV variable to properly reflect composite cost. It may be added that the mode choice model used for evaluating short term transport policy patronage effects need not be the same as that used for linking with the destination choice model. For this latter purpose, a less-refined mode choice model may be quite adequate.

To test the validity of these arguments, and whether the problem had been correctly interpreted, two strategies to overcoming it were devised. These fall considerably short of the full segmentation approach suggested above, but are more sensible for hypothesis-testing, as model development and estimation is extremely and unnecessarily time-consuming for that purpose. Results are reported below.

Destination Choice Model with Revised Inclusive Value Variable

The first strategy involved the calculation of the inclusive value using only the level-of-service variables, and their parameters as estimated in the full mode choice model.

This approach is somewhat suspect, because without models segmented by relevant SE characteristics, it is not clear to what extent the LOS parameters are influenced by included SE variables. However, if the effect of the SE influences is basically on captivity and habit, rather than through differential evaluations of the LOS variables, this approach should give reasonable values of the necessary composite cost variable. Without further analysis, this question cannot be fully resolved. Nevertheless, it was a simple way to test the effect of excluding SE variables from the calculation of inclusive value.

The second involved the re-estimation of the mode choice model, using only level-of-service variables (and constants) in the utility functions. While the results of this new model are not central to the discussion, it is of interest to compare the relative performances of the two mode choice models. The performance measure used is simply the sum of the absolute differences between observed and predicted mode use, for each alternative, summed over all origin-destination pairs.

Sum of absolute differences

	<u>Car Driver</u>	<u>Car Passenger</u>	<u>Public Transport</u>
Total trips in sample	217,016	37,090	93,804
Full model	21,156	7,966	20,809
Model based on LOS measures alone	42,884	8,954	42,258

Quite clearly, a major reduction in model performance has resulted, as expected. This would probably be improved were segmented level-of-service models to be developed, but for the exploratory purposes outlined this was not worthwhile.

The results of each strategy are given below, together with the original models using the inclusive value from the full mode choice model. Two models for each are presented, one with the inclusive value term alone, and the second including a distance variable, as previously discussed. The model form is as previously defined.

	<u>Parameter Estimates</u>		<u>Residuals</u>
	β	θ	
Model 1, C_{ij} = Time	-0.099	n.a.	222,300
Model 2, C_{ij} = Distance	-0.134	n.a.	227,139
Model 3, IV from full mode choice model; C_{ij} = distance	-0.116	0.274	227,322
	-	1.658	284,536
Model 4, IV from LOS variables only of full mode choice model; C_{ij} = distance	-0.058	1.068	213,315
	-	1.767	223,306
Model 5, IV from reduced mode choice model using LOS variables alone; C_{ij} = distance	-0.072	0.413	215,243
	-	0.787	238,505

Using full MC model, IV from LOS variables alone:

In this strategy, the inclusive value variable was created from only the level-of-service variables, using the parameters estimated in the full MC model. If the IV term alone is used in the model, the parameter estimate is unacceptably high, but model performance has improved

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dramatically over that when socio-economic variables were used to compute the IV variable. This by itself attests to the validity of using only LOS variables; taking their parameter from an MC model that also includes SE variables may, however, introduce some biases. This is probably the major reason for the high parameter value. When distance is included, a further major improvement in model performance is achieved, and Θ (1.07) is almost acceptable.

IV from reduced (LOS variables only) MC model:

This approach yields acceptable parameter estimates for Θ , but when the IV variable alone is used in the model, performance is not satisfactory. Including distance gives a marginally inferior performance to the previous approach, but one which is still a significant improvement over the previous "best" model (Model 1) that takes no account of the composite utility from the mode choice model.

Conclusions

A number of significant conclusions can be drawn from the foregoing, which are relevant to all MNL models of destination choice whether based on aggregate or individual data. For brevity, these are made in point form.

1. Conventionally, destination choice models of MNL form do not include alternative specific constants. This follows experience in the use of individual data, for which it is not appropriate to use ASC's for unranked alternatives. (Unranked alternatives arise when choice sets differ across individuals; alternatives must then be generalised by describing them only by their attributes). In the context of this work, however, this restriction does not apply, and ASC's are theoretically required. Their use makes the model identical to a conventional doubly constrained gravity model, removes the map-specificity or structural dependence of parameters, and dramatically improves the performance and spatial transferability of the model.
2. A significant improvement in destination choice model performance is achieved when the interdependency between mode and destination choice is taken into account. The conditionality of mode on destination choice for the work trip is supported.
3. A mode choice model incorporating socio-economic variables directly in its utility functions cannot be used for the computation of an inclusive value variable. Socio-economic influences may seriously distort the measure of "composite cost" being sought, and will result in unacceptable parameter estimates and model performance.
4. The appropriate way to compute the inclusive value variable is from a set of mode choice models estimated for relevant market segments, and based only on level of service variables.
5. There is no reason why the mode choice model used to estimate modal patronage should be the same as those used in the calculation of inclusive value. Hence separate models may be developed. Those used for the calculation of inclusive value may be inferior in performance to those used in patronage estimation, but they will, if properly specified for the separate purpose, be much better suited for the demands placed on them by the destination choice model.

6. It appears that the inclusion of distance as well as composite cost in the destination choice model gives a fuller specification of the effect of separation than does composite cost alone.

What has become the traditional problem in destination choice model estimation may be substantially avoided if the approach outlined above is used.

APPLICATIONS OF MODELS BASED ON CENSUS DATA

In suggesting potential application of models of the type developed, some caveats must be sounded. Firstly, because the data relates only to the work-trip, only this purpose can be modelled. Consequently, transport policy questions which do not impinge significantly on travel for this purpose cannot realistically be analysed using such models. However, because most peak hour public transport travel is work related, and because it is this system that is of most concern to public transport planners, the limitation may not be too great. Both road and public transport system capacity and performance is largely determined by peak demands, and hence in large part changes affecting either can be examined using work-trip models.

Secondly, the models presented are not at their full potential. In particular, there remain problems with the network data used, which until corrected will affect the sensitivity of the mode choice model to system changes. Also, it is highly desirable that the "public transport" mode be expanded to include the separate P/T modes. The analysis of small or localised changes can not sensibly be undertaken with the models as they currently stand.

But it is clear that these problems could be overcome, and a range of possible applications exist, that are simply noted below.

Fare policy analysis:

The patronage effects of changes in public transport fare policies are readily estimated, using the base data on which the models were estimated (the most recent Census data), and the mode choice models developed. The likely impact on trip distribution of such changes, if sufficiently significant, can also be assessed.

Major level-of-service change effects:

The mode and destination choice models can be used to assess the effects of significant changes in travel time. Minor changes, due to changed public transport frequencies, for example, are unlikely to be picked up unless good quality public transport network data is available for model estimation. This should be a high priority area for agencies interested in such policy questions.

Effects of new facilities:

The models are well suited to the evaluation of new facilities. Horizon-year socio-economic distributions must be predicted (as for all such exercises), and used as input to the models. Because generated travel can not be predicted, the models will under-estimate demand for and benefits from such facilities. The likely effects on employment locations and on car ownership levels may also be examined (car ownership models have been developed, but are not reported herein).

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Corridor studies

The models are ideally suited to sketch planning applications, and because they appear to be insensitive to the level of aggregation, their spatial transferability will materially assist in corridor study application.

For validating models based on individual data

The robustness of the models makes them useful as a benchmark against which models based on individual data, which may be more useful for detailed or localised analysis, can be checked. This opportunity alone justifies their development.

OVERALL CONCLUSIONS

It is easy for researchers to exaggerate the performances of their models, the excellence of their approaches, the universality of their data sets, or the superiority of their intellectual skills. But in this essentially pragmatic study, such claims are not warranted. Census data, limited as it is in focus and scope, will never provide a base for the range of models that can be developed from a skilfully designed, sensitively administered and meticulously processed household survey, regularly updated and administered by a team of professionals fully versed in the variety of skills necessary for this, and for model development and application.

Unfortunately, these conditions are never fulfilled. In the absence of useable data sets and/or forecasting models, Census data and the models that can be developed from it can be of considerable use. The models have been shown to be robust and well performed. They can be regularly updated as new data becomes available. They can be applied in a variety of spatial schemes, and are therefore suitable for sketch planning purposes. Questions of geographic and temporal transferability can be explored, because of the consistency of the data between cities and over time. They have a wide range of applications, despite the limitations inherent in models relating only to the work trip. And in comparison with models based on individual data, which is expensive to collect, they are cheaply developed.

It is apparent that the MNL modelling framework is well suited to the data set, despite potential problems associated with using aggregate data. The problem of the correct linking of mode and destination choice models has been overcome, which allows the influence of transport environment changes on destination choice to be assessed.

It is to be hoped that the very considerable potentials that have been shown to exist will be properly exploited in the future, so as to improve our presently extremely limited capability for rational transport policy analysis.

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