An Econometric Model of the Modal Choice of Sydney Work Trips

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ABSTRACT

The paper briefly discusses the problem of modelling choice of transport mode in the context of the broader range of travel decisions, and goes on to specify the structure of a binary choice model for work trips.

The model is estimated with data collected by the Sydney Area Transportation Study. Equations are estimated using data aggregated over geographical zones and disaggregated data.

The relationship of the work reported in this paper to previous work is indicated.

INTRODUCTION

It is common practice in urban transportation studies to analyse the travel patterns of a particular city at a particular point of time and to use this analysis for predicting future patterns and for comparing the effects of different transportation policies.[1] Another possible

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* Mr J. Toms of the BTE developed the computer programs for extracting the data for the SATS files and translating it into a form suitable for estimating the models.

1. For examples see Talvitie (1973), Shepherd (1972), Lave (1969) and Hensher (1972). There are numerous other instances including the application of the standard Urban Transportation Study procedures to cities throughout the world.

product of the analysis is the implications for the values travellers place on various travel characteristics such as travel time. We shall be following this approach for a very restricted range of travel behaviour in this paper. We shall be looking at CBD work trips using data collected by the Sydney Area Transportation Study. Furthermore we shall be concentrating only on the modal choice aspect of these trips.

The next section contains a brief discussion of two sorts of problems which occur when modelling travel: (i) those which arise because of the variety of decisions embodied in a particular trip, and (ii) those arising because of disequilibrium behaviour. This will be followed by a detailed discussion of the model used to describe modal choice, and a description of the data base with which the model is to be estimated. Finally we shall report on the econometric estimation results for CBD work trips, noting in passing the major differences between the models which are estimated here and a previous model using a similarly constructed data base (from the Melbourne Transportation Study).

The results show, not surprisingly, that control of privileged parking is the most effective way of influencing the modal choice of the work trip to the CBD. Nevertheless commuters do respond to the travel times and costs of the modes. Probably the most interesting conclusion is that CBD workers are far more sensitive to changes in public transport travel time than car travel time because public transport travel is regarded as much less comfortable. This is not brought out by most of the other studies in this area. The responses to these two changes are invariably constrained to be equal.

TWO ASSUMPTIONS

A variety of decisions lie behind the making of any particular trip. A person must decide from where and to where he shall make the trip. He must decide when (at what time of day) to make the trip, how often to make it and what mode he will use. It can be seen that estimating the demand for trips with so many characteristics is highly complex. The difficulties can be reduced by making simplifying assumptions which allow the factoring of the demand function into its component decisions. A fundamental characteristic by which all trips should be categorised is trip purpose. For example work trips should be handled independently of shopping trips and recreational trips should be a further separate category. The reason for this is that the weights with which attributes enter the decision making process will differ for different trip purposes. For a particular trip purpose, the validity of estimating separate functions for the various component decisions about a trip (frequency, time, mode, origin and destination) depends on the assumption that the marginal rates of substitution between the attributes determining each decision are independent of the other decisions. For the modal choice decision the MRS's between modal attributes are independent of the decisions about the time, frequency, origin and destination of the trip. For the work trip the timing and frequency decisions are usually institutionally constrained thus reducing the area over which the assumption must hold.[1]

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1. This assumption is discussed in detail in a report by Charles River Associates Incorporated (1972)

The transport planner is interested in the rate at which persons adjust their behaviour to changes in factors affecting their tripmaking as well as their ultimate equilibrium behaviour. Unfortunately the data available for estimating travel behaviour is usually cross-section data with no time series component. This means that we require the assumption that travel patterns are in equilibrium. This would be approximately true if the speed of adjustment to new situations was relatively rapid compared to the time periods between initiating changes and data measurement. We could then forecast changes in equilibrium conditions. Where the assumption is not true we cannot estimate equilibrium behaviour and we cannot make satisfactory forecasts of travel patterns without using time series information. This problem is obviously more acute for some types of behaviour than others. Thus decisions about the origin and destination of work trips (where to live and where to work) will react much more gradually to changes in factors affecting them than decisions about modal choice. In looking only at modal choice we have probably largely circumvented this problem.

DERIVATION OF THE MODAL CHOICE MODEL

The choice of mode for a work trip depends on the individual's perceptions of the various attributes of the modes from which the choice is made. These perceptions in turn depend on the physical determinants of these attributes, and the characteristics of the individual and his household.

Cost, time, comfort and convenience are the usual modal attributes considered. Many aspects of comfort and convenience are difficult to measure physically. We shall be concerned primarily with cost and time components in this study. Most commonly, choice of mode is made a function of the total costs of the chosen and alternative modes and the total times of the modes.[1] Some researchers have broken up the total times into in-vehicle times, access times and waiting times, on the hypothesis that travellers value these times differently because of the different circumstances in which the times are spent.[2]

The socio-economic characteristics of individuals and households which influence choice will operate either as direct constraints on the traveller's choice or through his evaluation of transportation attributes. Car availability could be interpreted as an example of a constraint - if an individual does not have access to a car he does not have an effective choice. On the other hand income will affect the value a person places on time savings rather than being an independent determinant of choice.

We use two types of variable to represent modal choice: (i) the proportion of work trips by public transport originating in a zone, and (ii) a dummy for each individual work tripper, equal to zero if he uses car and one if he uses public transport. The first variable is used in a zonal aggregate model in which observations correspond to geographical origin zones. The independent variables must of course be zonal averages. We miss all the intra-zonal variation in this sort of model. Each individual is a separate observation in the second case above, and there is scope for making use of intra-zonal variation, depending on the nature of the data we have at our disposal.[3]

1. See for example, Lave (1969)
2. See Talvitie (1973) and Hensher (1972)
3. In the Australian context, Shepherd (1972) has estimated zonal aggregate equations using data from the Melbourne Transportation Study, and Hensher (1972) has estimated disaggregate equations using data provided by his own specially designed survey.

We shall leave further discussion of the nature of the variables and the SATS data to be used in estimation until later, and turn now to the problem of the mathematical form of the choice expression.

Our current study is limited to choice between car (driver) and public transport. Trips by other modes (cycle, car passenger, walk) have been omitted; and we have not (yet) examined choice between different forms of public transport (train, bus, ferry). Thus we are looking at a binary choice model.

An individual will choose between the two modes according to the sign of the utility difference yielded by the modes. An empirical model used to describe this choice must be probabilistic either because the researcher can't measure an individual's utility exactly or because the individual's choice is itself probabilistic rather than deterministic.[1] Thus we have as our model that the probability of choosing a particular mode is some function of a measure of the utility difference between the modes.

We shall assume that the utility given by a mode (sometimes expressed as a generalised cost) is a linear combination of the modal attributes. Then we have,

$$\text{probability of choosing public transport} = P_{pt} = f(\Delta U)$$
$$= f(a.C_1 + b.T_1^1 + cT'' - dC_2 - eT_2^1 - fT_2'')$$

1. These two alternative assumptions are the postulates from which two theoretical structures are developed, each leading to a similar expression for the probability of choice between alternatives (Stopher (1974))

where, subscript 1 refers to the car mode
" 2 " " " public transport mode

ΔU = Utility difference between modes

C = cost

T^1 = in-vehicle time

T'' = access, egress and wait time

The implications of the linearity assumption are that the value of any one attribute in terms of any other attribute is constant for all attribute levels. Thus the value of saving a unit of travel time on public transport in terms of extra cost of public transport[1] is $\frac{e}{d}$ whether the trip takes 10 minutes or 40 minutes.

Most model builders have constrained the coefficients so that a = d, b = e and c = f. Assuming that the measures of variables are those perceived by the travellers, the first constraintis perfectly reasonable; it is the difference in costs which determines choice. The second constraint, however, is unlikely to be supported by actual behaviour.[2] The reason for this is that public transport travel will differ from car travel in the circumstances under which the travel time is spent. Since the impact of comfort is not brought explicitly into the model, its only influence is through the size of the coefficients of travel time. We shall therefore not apply the equality constraint on the in-vehicle travel times. With regard to the out-of-vehicle times, it is probably again unwise to apply constraints on the coefficients.

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1. This value is obtained by equating the changes in public transport patronage due to a change in PT cost and a change in PT travel time

2. This constraint is discussed in more detail in a short paper by the author (1974), which looks at Hensher (1972, 1973) on the subject of the valuation of travel time savings. Its relaxation has important implications for policy as we shall see later on in the paper.

There are several ways of including the effects of the socio-economic variables in the model. To the extent that they influence people's evaluation of transport characteristics, they should be embodied in the coefficients of the transportation variables, either directly in a single equation or by running separate equations for different socio-economic groups. It is often suggested that the higher a person's income the higher the value he puts on time savings. This means that the coefficients of the various components of time increase with income. There are several other hypotheses related to the role of income which could be tested, but this paper reports only on equations with income included multiplicatively with time variables on the assumption that time valuations are directly proportional to income. Factors such as the traveller's status in the household, car ownership, and age should probably be included linearly.[1]

$$P_{pt} = f(a.\Delta C + b.Y.T_1^{1} + c.Y.T_1^{"} - e.Y.T_2^{1} - f.Y.T_2^{"} + g.ST + h.A \text{ etc})$$

where Y = travellers income

ST = position in household (e.g. head, spouse)

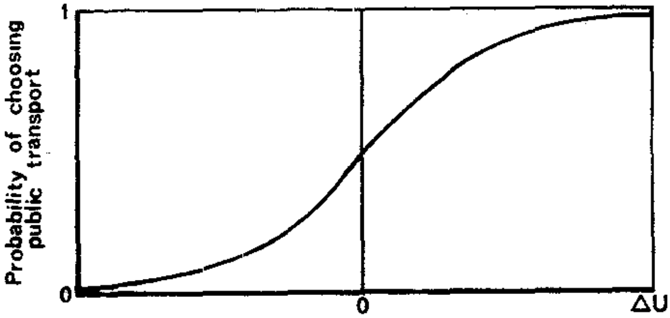
A = age

We come now to consideration of the form of f( ). This bears on the question of the method of estimation of the model. If there is a direct linear relationship between the independent variables and the choice variable we can use ordinary linear regression. This may be approximately true for a limited range of variation of the independent variables. Then the probability of choosing public transport is directly proportional to the explanatory variables. If there is substantial variation in the implied (or predicted) probability

1. De Donnea (1971) has an extensive discussion on the role of user characteristics in modal choice.

over the range of observations then linear regression involves two problems. The first is that the predicted probability may be outside the acceptable range of zero to one for some of the observations. The second is heteroscedasticity; i.e. the variance of the error term varies with the level of the predicted probability. This results in inefficient estimates of coefficients and misleading 't' statistics. To overcome these problems we can use the logistic transformation,

$$P_{pt} = \frac{e^{\Delta U}}{1 + e^{\Delta U}}$$



This curve accords with a priori notions on the nature of f( ). A change in ΔU in the situation where one or other of the modes has a very strong advantage is not likely to effect the probability of choosing a mode nearly as much as where the two modes are more competitive (i.e. where ΔU is close to zero).

The estimation of the logit function is complicated. Theil (1971) has re-expressed the relation, $\ln \left(\frac{P_{pt}}{1 - P_{pt}}\right) = \Delta U$. He then suggests grouping observations into groups as homogenous as possible with respect to the explanatory variables within ΔU and replacing P_{pt} with the relative frequency of choosing public transport for each group. A weighted least squares regression can be run on the grouped observations, the weights being determined from an expression he develops of the variance of the error term as a function of the number of observations and the relative frequency for each group.

An alternative technique, used by De Donnea (1971), is the maximum likelihood estimation method. This requires a programme for solving a set of non-linear equations in order to obtain the parameter values which maximise the likelihood function.

THE DATA

SATS carried out a large household survey which obtained a great deal of information about the characteristics of trip makers and their households and the details of the trips which they actually took. Unfortunately no information was collected from the individuals about the alternative choices open to them for a particular trip. However times and costs by mode between zones were synthetically constructed by the SATS team, and we use these in all our models. This means that we lose an important source of intra-zonal variation and our precision of choice explanation is thereby reduced. Ideally we need travellers' perceived times and costs for use in a disaggregate model of choice but these are not available from SATS.

A major problem with a modal choice model of trips to a single destination, such as the CBD, is the specification of the role of parking. This is related to the problem above because the effect of parking should be included as a perceived car egress time (time of parking and walking to place of work) for each individual. The synthetic SATS data on this variable is close to being a constant for all work trips ending in the CBD (some variation arises because our definition of the CBD includes several SATS traffic zones), and is not very helpful for our purposes. There is however information on the type of parking available to a CBD worker - whether or not he can park in a company park or on a reserved property. We can use this as a proxy for car egress time in the disaggregate model.

Data for the socio-economic variables, income, status in household, age, etc., is available for individual tripmakers from the household survey and this results in a substantial advantage for the disaggregate model over the zonal aggregate model.

The analysis of the SATS data involved separating out the CBD work trips from the "all trips" file, and matching individual and household characteristics and mode choice information with the synthetic time/cost information on the "mode split" file. Then we further eliminated those trips for which (i) household income was not given, (ii) distance by car from origin zone to the CBD was coded as zero, and (iii) a means of transport other than bus, ferry, train or car driver was used. Where work journeys included use of both car and public transport, the criterion for classifying by mode was the respondent's view of his main mode.

ESTIMATION OF THE MODEL

At this stage all equations have been estimated with a linear regression program and interpretation is therefore subject to the reservations expressed earlier. We are currently preparing to re-estimate some of the equations with a logit program using the maximum likelihood technique.[1]

1. Dr Peter Stopher, Northwestern University, has kindly provided us with this program.

Equations A and B in Table II are zonal aggregate equations in which the dependent variable is the ratio of public transport CBD work trips to the total of car and public transport CBD work trips for 472 origin zones in the Sydney area. The denominator of this ratio is about 92% of total CBD work trips, the other 8% being trips by other modes.

Shepherd (1972) has separate equations for car and public transport, and his dependent variables have the number of workers in a zone for the denominator rather than the number of workers travelling to the CBD. He then includes an an explanatory variable the ratio of labour force employed over labour force resident in the origin zone to account in part for the proportion of workers who go to the CBD. Shepherd's approach also allows the possibility that changes in the other explanatory variables (transportation and socio-economic variables) cause a change in the proportion of workers in a zone going to the CBD. Both these effects concern location decisions which require much fuller explanations in separate models. In this connection, we noted earlier that the dynamic responses of location choice and modal choice to changes in the transportation system (for example) will be very different.

Our model forces constraints on the relative responses of car and public transport usage when an explanatory variable changes. A change in the demand for car trips is balanced by an equal and opposite change in the demand for public transport trips. Shepherd's model consisting of two independent equations, has no such constraint and in fact the two responses vary widely. On the other hand our model does not force a fixed relationship between the time and cost coefficients while Shepherd imposes an externally determined time valuation which is the same for all time components. One further point of contrast is the inclusion of income multiplicatively with transportation variables in our model instead of linearly as in Shepherd's.

The coefficients of equations A and B are generally significant. The weakest variable is public transport access time. The intra-zonal variance is the most important source of variation in access times but this is not available to us from SATS. We need measures or perceptions of the individual travellers to identify more accurately the effect of this factor.

A feature of the equations is the very large positive constant term. The reason for this is that the effect of car egress time (parking and walking to place of work) has been omitted. It is very difficult to account satisfactorily for this factor in a model where the CBD is the only destination and the synthetic measure of car egress time shows very little variation. We attempt to get around this problem in the disaggregate model discussed later.

The relative sizes of the coefficients for car and public transport run times suggest that people place a higher value on, and their choice behaviour is more strongly affected by, reductions in public transport travel times than in car travel times. According to equation A, the value of time savings is 50% higher for public transport than for car. The time values implied by this equation are 3.6 cents per minute for car travel and 5.4 cents per minute for public transport. However the faith in these values should be tempered by the belief that time valuations should be estimated from analysis of the <u>perceived</u> times and costs of the subset of tripmakers who are faced with either a cost disadvantage or a time disadvantage on one of the modes.

The elasticities of the proportions using public transport and car with respect to the various transportation variables will be functions of these variables and the proportions themselves. Thus the elasticity of the public transport proportion with respect to public transport run time is given by $\frac{\partial P_{1PT}}{\partial PTRUN} \cdot \frac{PTRUN}{P_{1PT}}$ where, for equation A, $\frac{\partial P_{1PT}}{\partial PTRUN}$ = .0057 and constant. The elasticities at the mean values from equation A are :

	CACO	PTCO	CARUN	PTRUN
P_{1PT}	.20	.06	.23	.26
P_{1CA}	1.04	.33	1.19	1.34

The elasticities for P_{1CA} (the proportion using car) are all larger than those for P_{1PT} by a factor of 5.2 because of the difference in mean proportions.

A comparison of equations A and B indicates that the inclusion of income improves the fit. In accordance with our earlier discussion income has been included multiplicatively with time so that it influences the valuation of time savings.

Equation C is a disaggregate equation in which the dependent variable is a dummy taking the value zero if the trip was a car trip and one if it was a public transport trip. The data for each individual is exactly the same in this equation as in the aggregate equations, and the only difference is in the weight given to each observation in the analysis. In the aggregate equations each trip from zones where the number of trips is very low is implicitly given an arbitrarily high weight. The accuracy with which the sample flow of trips reflects the total flow from a zone will be less for zones for which the sample flow is low. This causes violation of the assumption of heteroscedasticity.

The final equation in table II is a disaggregate equation in which the income variable takes unique values for each individual instead of zonal average values. The times and costs remain zonal averages.

TABLE 1

Variables Included in the Models

T_{pt} = sample number of work trips from origin zone to CBD by public transport

T_c = sample number of work trips from origin zone to CBD by car drivers

$P_{1PT} = \dfrac{T_{PT}}{T_c + T_{PT}}$ for an origin zone

P_{2PT} = (1 for a public transport work trip to CBD
(0 " " car driver work trip to CBD

PTCO = average public transport fare from origin zone to CBD (cents)

CACO = average car cost from origin zone to CBD including fuel costs and parking charges (cents)

ΔC = PTCO - CACO (cents)

PTRUN= average time in public transport vehicle travelling from origin zone to CBD (minutes)

PTACC= average time travelling to and from the public transport terminals (minutes)

CARUN= average time in car travelling from origin zone to CBD (minutes)

Y_1 = household income per resident averaged over the origin zone

Y_2 = household income per resident applicable to the individual making the trip

REL = (0 if the tripmaker is the head of the house
(1 otherwise

AGE = (0 if the tripmaker falls in the age group 25-54
(1 otherwise

PTYP = (0 if the tripmaker has access to a company car park or
(a park on reserved property
(1 otherwise

TABLE II

A. $$P_{1PT} = \underset{(23.5)}{.80} - \underset{(5.5)}{.00106}\,\Delta C - \underset{(1.04)}{.0037}\,PTACC - \underset{(4.9)}{.0057}\,PTRUN + \underset{(6.1)}{.0038}\,CARUN$$

$R^2 = 0.132$

B. $$P_{1PT} = \underset{(41.9)}{.81} - \underset{(5.4)}{.00101}\,\Delta C - \underset{(2.8)}{.000106}\,Y_1 \cdot PTACC - \underset{(6.3)}{.000081}\,Y_1 \cdot PTRUN + \underset{(7.2)}{.000058}\,Y_1 CARUN$$

$R^2 = 0.174$

C. $$P_{2PT} = \underset{(50.1)}{.88} - \underset{(8.3)}{.00096}\,\Delta C - \underset{(3.9)}{.000081}\,Y_1.PTACC - \underset{(7.2)}{.000050}\,Y_1.PTRUN + \underset{(6.09)}{.000023}\,Y_1.CARUN$$

$R^2 = 0.079$

D. $$P_{2PT} = \underset{(47.2)}{.86} - \underset{(7.2)}{.00090}\,\Delta C - \underset{(3.3)}{.000059}\,Y_2.PTACC - \underset{(7.5)}{.000049}\,Y_2.PTRUN + \underset{(5.6)}{.000021}\,Y_2.CARUN$$

$R^2 = 0.078$

The equations in table III include further variables which vary with the individual rather than the zone. The binary dummy describing whether or not the individual is head of the house is strongly significant. This variable acts as a restriction with the head of the house having first claim on the use of the family car. We have also used a dummy variable to represent age. It is hypothesised that young people will tend to lack finance to buy and run their own car,[1] and old people have a bias against driving a car especially in peak traffic.

We turn our attention now to the strongest explanatory variable in the model, parking type. It is a dummy describing whether or not the commuter has a free and convenient park available to him in the CBD. It is therefore a proxy for the egress time and cost for the car mode, and probably also for other factors such as the need to use the car during the day. Unlike the other transportation variables, parking type relates to the individual rather than the zone. Its inclusion results in a large reduction in the constant term which becomes insignificant at the 5% level, and a big improvement in the R^2.

Another feature of the equations in table III is the separation of the car and public transport costs into separate variables. The coefficient in PTCO is smaller and less significant than the coefficient of CACO. There are several possible explanations of this, related to differences between commuters' perceptions of trip costs and the synthetic measures of costs constructed by SATS. The synthetic measure of public transport fares is based on the full single fare. Many train users buy weekly tickets at a somewhat lower average trip cost than the single fare. The difference between the weekly and single rates increases with journey distance and for the great bulk of the commuter trips averaged about 10% in 1971. This has two effects: (i) biases downwards the coefficient of fares; (ii) increases the variance of the estimated coefficient.

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1. Note that the income variable is household and not individual income.

There was a large change in public transport fare structure in the middle of the survey period. PTCO incorporates this change. However because most people would have adjusted their mode choice behaviour in response to these changes with a time lag, there will be errors in our comparative statics approach and again the precision of our estimate of the coefficient of fares is adversely affected.

Finally it should be noted that synthetic car costs include parking and fuel costs. Some of the other costs associated with running a car, particularly maintenance costs, may also be included in the perceived car cost for the commuter trip.[1] This would mean that our coefficient is biased, particularly if there was strong correlation between the omitted and included components of perceived cost.

The foregoing discussion has looked at the effects of measurement errors in the cost variables on the OLS estimates of the structural parameters corresponding to the "true" variables. It is thought that these errors are responsible for biases and the consequent divergence from equality of the two coefficients. More research is needed to verify this hypothesis. It may be possible, by using an adjusted estimation technique and making some reasonable assumptions about the errors, to go some way towards removing the biases.[2] However it is important to appreciate that the OLS estimates may still be appropriate for predicting choice using the measured variables. That is, the existence of the biases discussed above does not necessarily imply bias in our predictions.

The disaggregate equations emphasise even more than the aggregate ones the difference in sensitivity to changes in public transport travel time and changes in car travel time.

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1. This is supported by evidence on perceived components of cost of car travel for the work trip collected by Hensher(1972) p.116.
2. Some of the econometric texts, such as Theil(1971) (see Chs. 11 and 12), take up these problems.

TABLE III

A.

$$P_{2PT} = \underset{(1.7)}{0.062} + \underset{(7.5)}{0.105\ \text{REL}} + \underset{(3.4)}{0.047\ \text{AGE}} + \underset{(25.6)}{0.73\ \text{PTYP}} - \underset{(2.0)}{0.00030\ \text{PTCO}}$$

$$+ \underset{(5.1)}{0.00075\ \text{CACO}} + \underset{(3.5)}{0.0000116\ Y_2.\text{CARUN}} - \underset{(7.6)}{0.0000417\ Y_2.\text{PTRUN}} + \underset{(.27)}{0.0000041\ Y_2.\text{PTACC}}$$

$$R^2 = 0.339$$

B.

$$P_{2PT} = \underset{(1.8)}{0.064} + \underset{(7.5)}{0.105\ \text{REL}} + \underset{(3.4)}{0.047\ \text{AGE}} + \underset{(25.7)}{0.73\ \text{PTYP}} - \underset{(2.0)}{0.00031\ \text{PTCO}} + \underset{(5.1)}{0.00075\ \text{CACO}}$$

$$+ \underset{(3.5)}{.000012\ Y_2.\text{CARUN}} - \underset{(8.0)}{.000041\ Y_2.\text{PTRUN}}$$

$$R^2 = 0.339$$

In fact they suggest that CBD commuters value a minute saved on public transport over three times as much as a minute saved in car travel. The problem of different perceptions of the physical measures does not apply to travel times with the same force as to money costs because time in minutes for a trip is spent directly and unambiguously and also because there are no sudden jumps in relative travel times. However, as we have already discussed, perception of the circumstances under which time is spent in public transport and car differ and this is the principal reason for the difference in the coefficients.

The elasticities at the mean values for equation B in table III (currently the most preferred) are:

	CACO	PTCO	CARUN	PTRUN
P_{PT}	.14	.018	.065	.17
P_{CA}	.74	.096	.34	.88

The elasticities of course vary between different origins. They depend on the levels of the transportation variables and the dependent variable. Trips from inner suburbs (especially public transport trips) will generally have lower elasticities than those in the table. The elasticities will be higher than average for trips from the outer suburbs.

Although our estimated modal split equation is undoubtedly identified and describes the determinants of demand, it cannot be used by itself for predictive purposes. It must be used in conjunction with equations representing the supply side. Clearly travel times, car cost, and car egress times are endogenous variables which must be explained by separate equations. Thus car travel times will depend on factors such as traffic flows, road width and number of intersections. Consider a policy of reducing public transport travel time by introducing an express service from a particular suburb to the CBD. The Modal split equation predicts a certain shift in demand away from private car towards public transport. Car time will decrease because of a reduced private car flow. The ultimate swing to public transport is therefore less than predicted by the demand equation alone.

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POSTSCRIPT

Since the paper was presented, the equations in Table III have been re-estimated on a subset of the original data set, using logit analysis as well as linear regression. Generally the same variables entered significantly with the correct signs.

On the basis of measures of the coefficients relating the probability of choosing public transport to the independent variables, parking type and public transpor run time are the transport attribute variables least affected by re-estimation. Their estimated impacts on modal choice for CBD work trips appear fairly robust, irrespective of the data set size and the estimation procedure.

However, the re-estimations suggest that the coefficients (and elasticities) of public transport fares and car times and costs may have been under-estimated in the paper. In particular, logit analysis resulted in a relatively large increase in the influence of public transport fares but it remained one of the weaker variables of the model in terms of the confidence with which its effect was measured.