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DIVERTING INTER-URBAN CAR USERS TO RAIL: RESULTS FROM A REVEALED PREFERENCE MODE CHOICE MODEL

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ABSTRACT

Wardman, M., Toner, J.P. and Whelan, G.A. (1994) Diverting Inter-Urban Car Users to Rail: Results from a Revealed Preference Mode Choice Model. *ITS Working Paper* **423**, Institute for Transport Studies, University of Leeds, Leeds.

This paper reports disaggregate mode choice models based on the actual choices made by business and leisure travellers on inter-urban journeys which involved crossing the Pennines. The models explain choices as a function of the times and costs of each mode and of train headway and interchange. The models are an extension of those previously reported by Oscar Faber TPA as part of their Trans-Pennine Rail Strategy Study, involving a more detailed examination of functional form and disaggregation by journey purpose.

The research reported here was undertaken as part of an ESRC funded project examining the potential for diverting inter-urban car and air passengers to rail. There have been very few studies of inter-modal interaction for inter-urban travel and therefore little is known about the cross-elasticities. The findings discussed here are based on a preferred functional form of mode choice model. The results for leisure travel are generally very satisfactory, with an important distinction identified between group and solus travel. However, we place more reservations on the results obtained from the business model.

KEY-WORDS: *Demand modelling; forecasting; mode choice; elasticities; revealed preference; business travel; leisure travel.*

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1. INTRODUCTION AND OBJECTIVES

The research reported here was undertaken as part of an ESRC funded project (R000233791) concerned with measuring the potential for diverting inter-urban car and air travellers to rail. This project will develop four models which examine inter-modal interaction. Two models will be aggregate models, respectively examining the volume of air and car travel and how these are affected by variations in relevant travel variables, particularly those relating to the attractiveness of competing rail services. The remaining two models are disaggregate and examine mode choices between rail and car and between rail and air.

This paper reports disaggregate models which aim to explain individuals' actual choices between train and car. They are based on data collected as part of the Trans-Pennine Rail Strategy Study which was conducted by Transportation Planning Associates (TPA), now Oscar Faber TPA, for a consortium of Passenger Transport Executives and County Councils (TPA, 1992a, 1992b). Whilst the Trans-Pennine Rail Strategy Study also examined choices between train and coach, we are here only interested in the interaction between train and car since the overall aim of the study is to quantify the effect of improved rail services on the demand for inter-urban car travel.

The aims of the research reported here were:

i) to further examine the functional form of the mode choice model, with particular emphasis on the properties of the own and cross-elasticities.

ii) to disaggregate the models by journey purpose

2. BACKGROUND: THE PREVIOUS RESEARCH

The previous models developed by TPA did not segment by journey purpose. However, we would expect the elasticities to vary by purpose and we here report separate models for business and leisure travel. A commuting model has not been developed since, with the exception of the South East, commuters form only a small proportion of longer distance travel.

TPA made considerable efforts to identify the appropriate functional forms of the mode choice models. These took the form of logit models, which are by far the most common means of analysing mode choice behaviour, and we will briefly outline the properties of this form of model.

In the choice between two modes (1 and 2), the logit model expresses the probability of an individual i choosing mode 1 (P_{i1}) as a function of the utility difference:

$$P_{i1} = \frac{1}{1 + e^{-\Delta U_i}} \tag{1}$$

where ΔU_i is the difference in utility between mode 1 and mode 2. The utility of a mode (j) is related to the observable characteristics of that mode and of individuals.

$$U_{ij} = f(\alpha_j X_j, \delta_i S_i) \tag{2}$$

X is a vector of modal attributes which influence choice and the α are the weights attached to these variables and which can differ between modes. S is a vector of socio-economic characteristics of the individuals with associated weights δ. The purpose of the modelling stage is to obtain estimates of the α's and δ's which provide the best explanation of the observed choices and provide the basis for forecasting mode choice in a range of different circumstances.

Relative valuations are normally expressed in monetary terms, that is, the value of travel time savings are expressed as a monetary equivalent of the benefit obtained. An individual's marginal monetary valuation of variable m for mode j is derived as:

$$= \frac{f'(X_{ijm})}{f'(X_{ijc})} \tag{3}$$

where c denotes cost and f' is the derivative of the utility function. The point elasticity of demand for mode j with respect to changes in the level of variable X on mode k is:

$$\eta^{j}_{ikx} = f'(X_{ik}) X_{ik} (D - P_{ik}) \tag{4}$$

where D equals 1 if j=k, and the term represents an own elasticity, else it is zero and the term therefore represents a cross elasticity. It can be seen that a logit model's elasticities depend not only on market share but also, in general, on the level of the variable for which the elasticity is being calculated.

The overall elasticity can be estimated for a set of representative figures for, say, a particular route, but is more correctly estimated as the weighted average of elasticities evaluated for each individual given the set of circumstances each faces. The weight is the individual's choice probability as a proportion of the sum of choice probabilities.

The conventional form of utility function is linear additive:

$$U_{ij} = \sum_m \alpha_{jm} X_{ijm} \tag{5}$$

whereupon any monetary value is a constant and is derived simply as the ratio of the coefficient on the variable in question and the cost coefficient. The elasticity function is:

$$\eta^{j}_{ikx} = \alpha_{km} X_{ik} (D - P_{ik}) \tag{6}$$

This utility function is adopted by default in studies of urban travel which form the vast majority of disaggregate modelling applications. This function constrains monetary values to be constant, which may not be appropriate. Of greater concern, particularly since we are primarily concerned in this study with elasticities rather than relative values, is that it implies very large elasticity variation, which may not be justified. This may be particularly inappropriate in studies of inter-urban travel where travel variables can have a very large range. For example, if we compared two flows which had the same utility difference, and hence the same P_k, but one had a rail journey time of four hours and the other a journey time of one hour, the journey time elasticity would be four times higher on the former flow! It would seem that imposing such properties on the elasticity function is likely to be undesirable, and its use requires empirical verification rather than adoption by default. The aim of the analysis should be to identify the form of the utility function, and hence elasticity, that best explains the pattern of behaviour apparent in individuals' mode choices.

TPA's starting position was to recognise that the standard linear additive function would imply substantial elasticity variation and therefore that it was essential to examin a range of different specifications of the utility function which yield elasticities with different properties. A particularly attractive utility expression is the power function:

$$U_{ij} = \sum_{m} \alpha_{jm} X_{ijm}^{\beta_{jm}} \tag{7}$$

It allows utility to increase with the level of a variable at an increasing, decreasing or constant rate. It implies an elasticity function of:

$$\eta_{ikx}^{j} = \alpha_{km} \beta_{km} X_{ik}^{\beta_{km}} (D - P_{ik}) \tag{8}$$

where D is as defined in equation 4. As β_{km} falls, the elasticity variation with respect to the level of X_{km} is dampened. The purpose of the modelling exercise is then to identify the set of β's which provide the best explanation of the choices individuals have made. As β tends to zero, the level of the variable has less effect on its elasticity. We can specify the model such that the level of the variable is only allowed to influence the elasticity through its effect on P_{ik}. This is when the variable is specified in logarithmic form. If the cost variables for each mode are entered in logarithmic form, the elasticity function for cost would be:

$$\eta_{ikx}^{j} = \alpha_{kc} (D - P_{ik}) \tag{9}$$

where α_{kc} is the coefficient associated with the cost term for each mode k.

TPA experimented with the power function but discarded it because "while the goodness of fit improves as β decreases, suggesting a better model, the value of time begins to show unacceptable variation" (TPA, 1992b). An alternative form of incorporating non-linear effects was adopted which involved the specification of interaction terms. In addition to specifying in-vehicle time (IVT), headway, interchange, out-of-vehicle time (OVT) and cost, in the linear additive form of equation 5, interaction terms formed as the product of IVT and cost and of OVT and cost were also entered. The level of cost therefore influences both the IVT and OVT elasticities, whilst the cost elasticity is influenced by the level of IVT and of OVT.

3. BACKGROUND: TRANS-PENNINE CHOICE DATA

Before reporting the results of models fitted to the actual choices of leisure and business travellers, we will briefly describe some of the characteristics of the data supplied to us by TPA. The data were collected in the summer of 1990. Car users were contacted at roadside surveys undertaken as part of the Trans-Pennine Road Study which was also conducted by TPA. Train and coach users were contacted during the course of their journey. The sampling was clearly not undertaken on a random basis and we need to determine how representative the sample is. The sample may be unrepresentative not only in terms of the proportion using each mode of travel but also the degree to which the modes are substitutes and indeed the extent to which alternative modes exist. Matters are not helped by the dearth of reliable, detailed information about the characteristics of the long distance travel market in Great Britain.

In terms of the returned questionnaires, 65% were for car users, 28% for train users and 7% for coach users. The figures would seem to be too low for car and too high for rail. Dodgson (1991) cites shares for longer distance travel based on the National Travel Survey 1985/86 of around 80%, 11% and 9%. We will take these latter figures as broadly representative of the overall inter-urban travel market.

Another issue is the extent to which alternative modes are available since this will affect the calculation of elasticities and the forecast demand changes. Individuals were asked whether it would have been possible to make the journey by other means of transport and, if they could have used more than one other means of transport, to select one of them to give details about for modelling purposes. We presume that the alternative mode given is the best alternative and we effectively assume that the probability of ever using a third mode where available is zero.

We have no way of checking the TPA figures relating to the break-down of the market according to choice set composition. However, it would seem reasonable to assume that the proportions within each mode are fairly accurate. The figures given in Table 1 are based on those contained in TPA (1992b), adjusted to ensure that the overall mode shares are an accurate representation of the inter-urban travel market but maintaining the relative proportions within each mode.

We take the 'no alternative' figures in Table 1 to mean that such individuals have a zero probability of using any other mode. This could come about either because there is truly no practical alternative means of transport or because no alternative would ever be considered. We are aware that the mix of these two types of response will have varied across routes; for example, the former will account for a higher proportion of the no alternative responses amongst car users for movements between rural origins and destinations where the public transport system is far from accessible. However, the information here is the best we have with which to decompose the market into different choices sets to allow the application of our binary choice models. If forecasting is being undertaken of, say, the impact of rail improvements on the demand for car where a rail service is clearly available, the best alternative figures will overstate the extent to which car users do not have an alternative and thus will underestimate the cross-elasticity estimate. However, we would not expect the underestimation to be serious since such flows form the majority of inter-urban trips and hence will have the largest impact on the proportions in Table 1.

We are also aware that the figures reported in Table 1 will vary according to journey purpose but we do not have more disaggregated data. This issue, and the uncertainties as to how the choice set composition might vary across flows with different characteristics, is a problem in the use of disaggregate choice models.

The figures given in Table 1 which characterise the long distance travel market in terms of its choice set composition seem reasonable. It is to be expected that a large number of car users consider themselves to have no alternative and that more car users cite train rather than coach as their alternative. It is also to be expected that fewer train and coach users claim to have no alternative and that car is available for a higher proportion of train users than coach users.

Table 1: Mode Used and Best Alternative

	Car Used (80%)	Train Used (11%)	Coach Used (9%)
Car Alternative	-	5%	3%
Train Alternative	24%	-	5%
Coach Alternative	14%	4%	-
No Alternative	42%	2%	1%

4. EMPIRICAL FINDINGS - LEISURE TRAVEL

We have taken the same view as TPA that the identification of the appropriate functional form relating choice to the independent variables is of critical importance. However, there are a number of differences between TPA's models and those reported here, most notably in terms of our segmentation according to journey purpose and adherence to the power function model. We have not specified interaction terms since, given the software available to us, the estimation of the power function model is in itself a complicated task.

The data set made available was that upon which TPA calibrated their models and it contains 679 leisure travellers. We eliminated 135 individuals who were making short distance journeys, defined as involving a one-way rail journey time of 30 minutes or less. Of the remaining 544 individuals, 326 (60%) chose car.

Various models were examined using as a starting point the linear-additive utility function of the form of equation 5. The independent variables which can be used to explain choice are train interchange, train headway, out-of-vehicle time (OVT), in-vehicle time (IVT) and cost. With one exception, we have not introduced socio-economic factors into the model. This is because the extra complexity involved in estimation is not rewarded in practical forecasting applications since information on socio-economic variables for each forecasting situation is either absent or very expensive to acquire.

At the outset, we have allowed for different coefficients according to whether the individual was travelling in a group or not, in addition to specifying cost in 'per person' units. This is because the sensitivity of demand to changes in travel characteristics may well differ between group and solus travel. Although it could also vary across different categories within group travel, such as those travelling with young children or according to whether costs are shared amongst the group or not, this level of detail was not available to us and in any event our sample size limits the extent to which more detailed analysis could feasibly be undertaken.

There was no material difference between the headway, OVT or, surprisingly, interchange coefficients when segmented according to group or solus travel. The IVT and cost coefficients were both segmented into four categories, according to group and solus travel and car and train. All four cost coefficients were statistically significant and there were some large differences between them. However, the IVT coefficients relating to train for group and solus travel were insignificant. Whilst we cannot be certain as to the cause of this, it is certainly implausible that rail IVT does not influence mode choice. The most likely explanation of this perverse result is the large correlations between the rail IVT coefficients and other coefficients; for example, a correlation of -0.844 between the estimated coefficients for train IVT and car IVT for those travelling alone and a corresponding figure of -0.737 for those travelling in a group. A single time coefficient was therefore specified, regardless of group or solus travel and making no distinction by mode of travel. The group travel effect is therefore represented within the utility function solely in the cost terms. Given that the OVT coefficient was found to be similar to the IVT coefficient, these two variables were combined into a single journey time figure in subsequent models.

The 7 variables contained in the model upon which detailed analysis is to be conducted are: headway and interchange, which are both specific to train; journey time, which has a single coefficient for train and car; and four cost terms representing the combinations of car and train cost and solus and group travel. All variables are specified in round trip units.

We have adopted the power utility function of equation 7 and the aim is to find the combination of β's with associated α's which provides the best explanation of individuals' observed mode choices. If the dependent variable was continuous, whereupon multiple regression would be appropriate, the technique of non-linear least squares would be used to simultaneously estimate the α's and β's. This procedure is available in standard statistical packages such as SAS. However, our logit estimation software (ALOGIT), although advanced in several respects, does not allow the direct estimation of utility functions which are non-linear in parameters. Instead we must adopt an iterative procedure of specifying various values of the β's, thereby constructing new independent variables to which α's are estimated, and search for the combination of β's which provides the best fit.

It soon became apparent that the β values which gave the best fit for car cost and for train cost for those travelling in a group were very similar. To simplify the search procedure, we therefore constrained these two β's to be the same by estimating a single β for group travellers for train and car cost ($\beta_{COST\text{-}G}$), although the α was allowed to vary between train and car. The combination of β's which provided the best fit and the associated log-likelihood are given in bold as the first row of Table 2. The next 11 rows show that any movement in units of 0.1 away from the values in the first row leads to a worse fit whilst the final row represents the standard linear-additive utility function.

Some interesting findings have emerged. There are three power terms relating to the cost variables and these terms dictate the extent of cost elasticity variation. $\beta_{COST\text{-}CA}$ and $\beta_{COST\text{-}TA}$ are for car and train cost for those travelling alone whilst $\beta_{COST\text{-}G}$ is for those travelling in a group and relates to both modes. $\beta_{COST-CA}$ shows that the car cost elasticity is somewhat less sensitive to variations in cost per person for those travelling alone than those in a group. The same is also true but to a lesser extent for the train cost elasticity. We would expect those in a group to be more sensitive to cost variations since larger income effects are involved in a given variation in cost per person for group travel. The absolute cost elasticities also depend on the α values, market share and the level of the variable and comparisons between group and alone travel are reported below.

Interchange is found to have a larger impact at higher levels of interchange, which is again plausible, whilst the time elasticity will be constant with respect to the amount of time. It is to be expected that the benefits to be derived from improving frequency will be greater where the frequency is poor and the results show a strong relationship between the level of headway and the headway elasticity.

Table 2: β Values for Leisure Model

β_{HEAD}	β_{INT}	β_{TIME}	$\beta_{COST-CA}$	$\beta_{COST-TA}$	β_{COST-G}	Log Likelihood
1.0	**1.7**	**LOG**	**0.7**	**1.1**	**1.4**	**-289.82**
0.9	1.7	LOG	0.7	1.1	1.4	-290.42
1.1	1.7	LOG	0.7	1.1	1.4	-290.67
1.0	1.6	LOG	0.7	1.1	1.4	-289.86
1.0	1.8	LOG	0.7	1.1	1.4	-289.84
1.0	1.7	0.1	0.7	1.1	1.4	-290.37
1.0	1.7	LOG	0.6	1.1	1.4	-289.99
1.0	1.7	LOG	0.8	1.1	1.4	-290.44
1.0	1.7	LOG	0.7	1.0	1.4	-289.83
1.0	1.7	LOG	0.7	1.2	1.4	-289.97
1.0	1.7	LOG	0.7	1.1	1.3	-289.85
1.0	1.7	LOG	0.7	1.1	1.5	-289.89
1.0	1.0	1.0	1.0	1.0	1.0	-301.32

Table 3 presents the coefficient estimates and, where appropriate, associated t statistics for the leisure travel model with the best fit. The four cost coefficients represent the combinations of alone (A) and group (G) travel and car (C) and train (T). The t statistics are quite acceptable given that we only have 544 observations and the goodness of fit is noticeably higher than the value of 0.177 obtained for the linear additive utility function. The highest correlations between estimated coefficients are -0.61 between Cost_G^C and Cost_G^T and -0.52 between Cost_A^C and Cost_A^T; no other correlations exceed 0.2.

Table 3: Parameter Estimates for Best Leisure Model

	α	β
ASC-CAR	-0.74471 (3.0)	
HEAD	-0.00402 (3.9)	1.0
INT	-0.04683 (2.5)	1.7
TIME	-1.34201 (4.9)	LOG
$COST_A^C$	-0.01265 (6.1)	0.7
$COST_A^T$	-0.00027 (4.2)	1.1
$COST_G^C$	-0.00009 (3.7)	1.4
$COST_G^T$	-0.00005 (3.2)	1.4
LL(M)	-289.82	
ρ^2	0.209	

Note: All variables are specified in round trip units. Costs are in pence per person and times are in minutes.

The alternative specific constant (ASC-CAR) slightly favours train. However, it must be adjusted to allow for the fact that our sample contains 40% rail users whereas from Table 1 we can see that the rail share amongst the market of those choosing between rail and car is 17%. The adjustment is required not only to ASC-CAR but also to that set to zero in the model (ASC-TRAIN). Following Coslett (1981) the correction to the constants obtained from a biased sample uses the following equation.

$$ASC_{Ai} = ASC_{Ei} - LOG\frac{s_i}{S_i} \tag{10}$$

where s_i is the sample market share of mode i, S_i is the population market share, ASC_{Ai} is the amended ASC for mode i and ASC_{Ei} is the estimated ASC. Amending the constants leads to an ASC-CAR of -0.423 and an ASC-TRAIN of -0.842, yielding a preference of 0.419 'utils' for car.

Given that the 'marginal utilities' generally vary according to the level the variable takes, the relative valuations, such as monetary valuations, are not constant. Table 4 therefore reports the marginal monetary valuations of each variable as an average across each individual's valuations. The marginal valuations are derived for each individual using equation 3.

Table 4: Marginal Monetary Valuations

	Headway	Interchange	ASC1	ASC2	Train Time	Car Time
ALL	5.69	236	596	348	7.92	7.36
ALONE	6.64	284	696	371	8.66	7.22
GROUP	4.49	169	470	319	6.99	7.54

Notes: All valuations are expressed in terms of the train cost units, with the exceptions of: ASC2, which expresses the constant favouring car in terms of car cost units; and the car value of time. The interchange valuations are based on those who experienced at least one interchange. The units are pence and minutes.

Although the average values of headway are lower than the corresponding values of time, they do appear to be too high. An improvement in frequency from 2 hourly to hourly on each leg of a journey would, on average across travellers, be valued at £6.82 given that the marginal value of headway is constant with respect to the level of headway. This seems implausible, although it is the elasticities which are of greater interest to this study. The value of headway is higher for those travelling alone because they are less sensitive to cost variations.

The values of interchange appear sensible and are in line with the conventional wisdom in this area, with again a lesser sensitivity of those travelling alone to cost variations leading to a higher interchange valuation. The values of the alternative specific constant (ASC1 and ASC2) seem reasonable and in both cases are higher for those travelling alone.

The values of time are fairly high but are by no means implausible and are certainly not inconsistent with the conventional wisdom in this area. For example, for data gathered in 1985, Marks and Wardman (1991) report a value of time of 5.32 pence per minute for inter-urban rail leisure travellers. Noticeably this study obtained a value of headway of 2.02 pence per minute which would seem to be a more plausible value relative to that for time than we have here obtained. More recent evidence, obtained in a study conducted by the Babtie Traffic and Transportation Consultancy and the Institute for Transport Studies on inter-urban leisure rail trips in East Anglia obtained a value of time of 5.81 pence per minute and a value of headway of 2.61 pence per minute. Both studies find the value of headway to be around 40% of the value of time. The implausibility of the valuation of headway obtained here should be borne in mind when using this model for demand forecasting, with consideration given to the much more convincing findings regarding the relative valuations of time and headway obtained in the two studies cited here.

We now turn to the elasticities implied by the model reported in Table 3. This will allow us to assess the model in terms of the plausibility of its implied elasticities and also illustrate the extent of elasticity variation across different travel contexts.

Table 5 presents all the direct and cross elasticities which can be estimated from our model. The superscript denotes the mode to which the demand variation relates. The first of the two subscripts denotes the variable and the second represents the mode to which that variable relates. The term η^{C}_{HT} therefore denotes the (cross) elasticity of car demand with respect to the headway of train.

The elasticities are calculated using the sample enumeration method. This is a weighted sum of elasticities calculated for each individual, with the weights being each individual's choice probability relative to the sum of choice probabilities. Estimates are given for the 312 solus travellers, the 232 group travellers and the overall sample.

Table 5: Leisure Choice Elasticities

	ALONE	GROUP	TOTAL
η^{C}_{CC}	-0.23	-0.14	-0.19
η^{C}_{TC}	-0.27	-0.18	-0.23
η^{T}_{CT}	-0.48	-0.59	-0.51
η^{T}_{TT}	-0.78	-0.95	-0.84
η^{T}_{HT}	-0.32	-0.39	-0.35
η^{T}_{IT}*	-16%	-19%	-18%
η^{T}_{CC}	0.66 (0.30)	0.73 (0.33)	0.68 (0.31)
η^{T}_{TC}	0.78 (0.35)	0.95 (0.43)	0.84 (0.38)
η^{C}_{CT}	0.17 (0.05)	0.11 (0.03)	0.14 (0.04)
η^{C}_{TT}	0.27 (0.08)	0.18 (0.05)	0.23 (0.07)
η^{C}_{HT}	0.11 (0.03)	0.08 (0.02)	0.10 (0.03)
η^{C}_{IT}*	6% (2%)	4% (1%)	5% (2%)

Note: * The interchange 'elasticities' represent the effect on car or train demand of each person having an additional interchange on each leg of their journey.

The first six rows represent own elasticities with the remaining six representing cross elasticities. In these final six rows we have given an adjusted figure in brackets on the basis that there will be a portion of rail (car) users who will not be affected by changes in the characteristics of car (rail). From Table 1, only 24/80 or 30% of car users have train as an alternative and hence for 70% of car users the probability in the cross-elasticity term of equation 4 is zero. Similarly, the probability term in the cross-elasticity is zero for 55% of rail users. This, of course, contains the implicit assumption that, for example, car users with coach as the best alternative are not affected by changes to rail. The figure in brackets is taken as most appropriate.

We have not adjusted the own elasticities since it is less straightforward to do so and indeed less essential that any adjustment is made. If, in the case of rail elasticities, the rail travellers with coach and no alternative have the same elasticities as those with car as their alternative, then the elasticities in Table 5 would be appropriate. Whilst it may be that the different market segments have different elasticities, in particular those with no alternative having lower elasticities, the figures in Table 3 are unlikely to be far out on this account.

Let us consider first the cross elasticities. These appear plausible. The cross-elasticity of car demand with respect to the characteristics of rail are all low (<0.1), reflecting the dominance of car in market share terms, whilst train demand is seen to be much more sensitive to the characteristics of car. These cross-elasticities show that reducing journey time would be a more attractive proposition to car users than reducing rail cost. The only concern we have is over the headway cross-elasticity which, in the light of the above discussion, may well be too large.

The own elasticities for car seem reasonable. The elasticities for group travel are lower because car achieves a higher share for group travel. The rail time elasticity is consistent with other evidence as is the effect of an additional interchange on the demand for rail travel. Although those with a car available can be expected to appreciate the convenience benefits of a car, and therefore may value headway highly, we have argued that the valuation of headway is implausibly high. It is therefore not surprising that the headway elasticity is somewhat higher than other evidence suggests and consideration should be given to using an amended value in forecasting applications. The rail cost elasticity for train does seem to be on the low side, but with those in a group being more sensitive to cost variations as would be expected.

When the headway coefficient is reduced to 50% of its current value, η^{T}_{HT} for the total sample is reduced to -0.18 whilst η^{C}_{HT} falls to 0.06 (0.02). These are somewhat more plausible, and the other elasticities do not vary a great deal as a result of this amendment to the headway coefficient.

Overall, the results of our model in terms of both the implied elasticities and relative valuations are encouraging with regard to the reliability of the model and to the application to forecast the impact of improved rail services on the demand for inter-urban car travel.

Table 6: Characteristics of Selected Flows

Flow	Distance	Car Time	Car Cost	Train Int	Train Head	Train Time	Train Cost
Blackpool-Norwich	253	265	1265	1	2 Hourly	410	2150
Manchester-Cardiff	196	184	980	0	Hourly	240	1500
Sunderland-Chester	193	200	965	2	2 Hourly	330	1650
Liverpool-Peterborough	171	185	855	0	Hourly	270	1400
Chester-Hull	142	140	710	1	Hourly	225	1200
Bradford-Leicester	109	114	545	2	Hourly	220	800
Leeds-Chester	88	90	440	1	Hourly	165	650
Manchester-York	77	81	385	0	Half Hourly	120	455
Bradford-Sheffield	43	53	215	1	Hourly	130	300
Leeds-Manchester	43	47	215	0	Every 20m	85	320

Note: All figures are for a one-way journey and are converted to a round trip prior to being entered into the model for forecasting.

Table 7 shows how selected point elasticities vary across different circumstances. These circumstances are depicted in Table 6 and were chosen to provide a range of different travel situations. The car times in Table 6 were obtained from the Autoroute package, with car costs taken to be petrol costs calculated at £2 per gallon and a fuel consumption of 40 miles per gallon. The train times include 30 minutes of access and egress time and the train fare is based on the Saver fare that applied in 1990. In the case of group travel, the costs are converted into per person units. This involved dividing the car costs by occupancy, with a child counting as half an adult, and the rail costs being deflated by a third on the basis of the survey data. The latter reflects the discounts for childrens' fares as well as other discounts available through family railcards. Although access and egress costs for rail are not included, nor have we included any costs other than petrol for car.

The first four elasticities reported in Table 7 are car and train cost elasticities for alone and group travel, showing not only how these elasticities vary across different travel circumstances but also how they relate to each other. The remaining four elasticities are specified for the total market, which from our data is made up of 57% solus travellers. These are the train time and headway elasticities and car cross-elasticities with respect to train cost and time. The final two columns report the predicted car shares for those travelling alone (S_C^A) and those in a group (S_C^G).

Table 7: Selected Elasticities for Leisure Travel

Flow	Alone		Group		Total					
	η_{CC}^C	η_{CT}^T	η_{CC}^C	η_{CT}^T	η_{TT}^T	η_{HT}^T	η_{CT}^C	η_{TT}^C	S_C^A	S_C^G
Blackpool-Norwich	-0.31	-2.51	-0.05	-4.58	-1.22	-0.88	0.08	0.03	0.85	0.98
Manchester-Cardiff	-0.67	-1.24	-0.17	-2.53	-1.02	-0.36	0.16	0.10	0.63	0.89
Sunderland-Chester	-0.21	-1.95	-0.04	-3.15	-1.25	-0.89	0.05	0.03	0.88	0.97
Liverpool-Peterborough	-0.52	-1.25	-0.12	-2.33	-1.06	-0.38	0.12	0.08	0.68	0.91
Chester-Hull	-0.37	-1.15	-0.08	-1.90	-1.12	-0.40	0.09	0.07	0.74	0.92
Bradford-Leicester	-0.22	-0.81	-0.05	-1.09	-1.17	-0.42	0.04	0.05	0.82	0.93
Leeds-Chester	-0.25	-0.60	-0.06	-0.78	-1.10	-0.40	0.04	0.07	0.76	0.89
Manchester-York	-0.38	-0.31	-0.10	-0.41	-0.92	-0.16	0.05	0.13	0.59	0.78
Bradford-Sheffield	-0.10	-0.28	-0.02	-0.27	-1.18	-0.42	0.01	0.05	0.84	0.91
Leeds-Manchester	-0.19	-0.25	-0.04	-0.26	-1.01	-0.12	0.02	0.10	0.70	0.81

Note: The cross-elasticity terms have been adjusted to account for those who would not be affected by the change in travel characteristics.

It can be seen that, except for journeys of the shortest distances that will concern us, the train cost elasticities are always higher for those in a group but that the reverse is the case for car. It can be quite clearly seen that the cost elasticities tend to increase with distance which is to be expected given that the power terms (β) are large for each of the cost terms. The journey time elasticity for rail exhibits relatively little variation as a result of the form that time enters the utility function. The time elasticities are high, but the elasticity to in-vehicle time will be lower according to the proportion that in-vehicle time forms of overall journey time. The headway elasticities are implausibly high, and this issue has already been discussed, but the figures do show the large variation in the headway elasticity according to the level of headway that is to be expected given the functional form of headway in the utility expression.

The cross-elasticities appear very plausible. Where rail offers an attractive service, such as between Manchester and Cardiff and Liverpool and Peterborough in Table 6, the cross-elasticities are higher whilst the cross-elasticity of car demand with respect to the cost of rail tends to be higher on longer distance journeys where the train costs are higher.

A desirable feature of the model is that it will tend to predict higher shares for rail for longer distance journeys for a given level of frequency and interchange. This is because the access/egress penalty of train means that doubling distance will not double journey time whilst the tapered fare structure has the same effect. On the other hand, doubling distance will double car costs and times.

5. EMPIRICAL FINDINGS - BUSINESS TRAVEL

The data set supplied to us by TPA contained 655 observations of business travel choice. We have omitted 73 cases involving rail journey times of 30 minutes or less, leaving 582 observations for modelling purposes.

The same procedure was followed in identifying the best business model as was done in the case of leisure travel and the results are reported in Table 8. There is no compelling reason to segment the parameters of a business travel model according to group or solus travel and thus we have just two cost coefficients. A single time coefficient is specified because of the large correlations between time and cost coefficient estimates when time is made mode specific in addition to cost. The time variable again includes in-vehicle time and access-egress time since initial models showed them to have similar valuations.

The best model constrains the β value for headway (β_{HEAD}) to equal one since increases in the value of β_{HEAD} brought continual increases in the goodness of fit. It is not clear why this happened, although it is not because of increasing correlations with the constant since large values of β_{HEAD} will lead to lower correlations between the headway coefficient and the constant.

With regard to the remaining four β's, there are some striking similarities with the leisure model, although the monetary valuations are somewhat different. The disutility of interchange is again found to increase more than proportionately with the number of interchanges and time again has a logarithmic form. Although we are allowing the β values for cost to be somewhat less than one, whereupon the cost elasticity variation with regard to the level of cost would be somewhat dampened, we again find appreciable cost elasticity variation according to the level of cost. The best model achieves a goodness of fit of 0.340, which is quite respectable and somewhat higher than the value of 0.319 for the conventional linear-additive model.

Table 8: β Values for Business Model

β_{HEAD}	β_{INT}	β_{TIME}	$\beta_{COST\text{-}CA}$	$\beta_{COST\text{-}TA}$	Log Likelihood
1.0	**1.4**	**LOG**	**1.0**	**0.7**	**-153.76**
1.0	1.3	LOG	1.0	0.7	-153.78
1.0	1.5	LOG	1.0	0.7	-153.78
1.0	1.4	0.1	1.0	0.7	-153.95
1.0	1.4	LOG	0.9	0.7	-153.80
1.0	1.4	LOG	1.1	0.7	-153.77
1.0	1.4	LOG	1.0	0.6	-154.11
1.0	1.4	LOG	1.0	0.8	-153.94
1.0	1.0	1.0	1.0	1.0	-158.65

Table 9 presents the coefficient estimates and, where appropriate, associated t statistics for the business travel model with the best fit. The t statistics are quite acceptable given that we only have 582 observations. The highest correlation is 0.77 betweeen the coefficient estimates for headway and the ASC but no other correlation of estimated coefficients exceeds 0.4.

Table 9: Parameter Estimates for Best Business Model

	α	β
ASC (CAR)	-1.47200 (3.7)	
HEAD	-0.00678 (2.7)	1.0
INT	-0.24410 (4.1)	1.4
TIME	-1.51500 (3.6)	LOG
$COST_C$	-0.00062 (1.6)	1.0
$COST_T$	-0.01431 (6.1)	0.7
LL(M)	-153.76	
ρ^2	0.340	

Note: All variables are specified in round trip units. Costs are in pence and times are in minutes.

80 (14%) of the sample of 582 business travellers chose rail. Table 1 shows that the market share of train amongst those choosing between train and car is 17%. However, Table 1 is inappropriate for business travel since coach will not enter the choice set. If we remove coach from consideration, and assume that the relative rail and car shares are the same as in Table 1 and that where coach is the alternative for car and rail users its proportion is split equally between car/train and no alternative, the proportion choosing rail from amongst those choosing between car and rail is around 18%. Thus any amendment of the ASC as specified in equation 10 would make very little difference to the market share forecasts and elasticities of the estimated model. We have therefore left the ASC unadjusted.

Before examining the implied elasticities, we will consider the marginal monetary valuations. We have again estimated average values across individuals given the circumstances they faced and these values are reported in Table 10.

Table 10: Marginal Monetary Valuations

Headway	Interchange	ASC1	ASC2	Train Time	Car Time
5.89	497	1276	2453	4.92	15.53

Notes: All valuations are expressed in terms of the train cost units, with the exceptions of ASC2, which expresses the constant favouring car in terms of car cost units, and also the car value of time. The interchange valuation is based on those who experienced at least one interchange.

The constant term favours rail to an implausibly strong degree and this may well have resulted from the large correlation with the headway coefficient estimate. The headway effect, as with the leisure model, would seem to be too high and to be here related to the problem with the constant since a large disutility surrounding train headway can compensate for a strong constant favouring train and the correlation between the headway coefficient and the constant is 0.77. The reported money value of headway is perhaps misleading because it depends on what appears to be a high sensitivity to variations in rail cost and we have therefore calculated the relative marginal valuation of headway in terms of time, at the journey time faced by each individual. This averages 1.39 but we do not feel that it is plausible that business travellers value travel time less highly than headway. Results reported in Fowkes, Marks and Nash (1991) show travel time to be somewhat more important than headway for business travellers whilst our own study of air business travellers, conducted as part of this ESRC project, also shows time to be more important than headway (Wardman, Whelan and Toner, 1994). We again conclude therefore that consideration should be paid to using an amended headway coefficient for forecasting purposes.

Given that the reported money value of interchange is also influenced by the high sensitivity to rail cost, we have calculated its journey time equivalent. This averages 128 minutes across travellers. We do not find it surprising that this is somewhat higher than for leisure travel.

Fowkes, Marks and Nash (1991) cite a value of time for business travellers of around 12 pence per minute at 1984 prices. This is equivalent to around 17 pence per minute at 1990 prices. However, it should be noted that the latter model was based on London bound business travellers who may be different, both in terms of the type of business trip being made and the seniority of the business traveller, to the sample here. The low value of train time in terms of train cost is clearly implausible as a measure of the extent to which business travellers would benefit from lower journey times. The low value of train time stems from the high sensitivity of demand to rail fares and this model is calibrated to provide an explanation of modal choice rather than an explanation of the value of time. We therefore need to examine the plausibility of the elasticities relating to train fare before drawing any conclusions, particularly since this study is more concerned with elasticities than with valuations. Nonetheless, the relative valuations derived from the business model are not as satisfactory as those derived from the leisure model.

The choice elasticities, calculated in the same manner as for leisure travel, are reported in Table 11. The effect of factors other than market share on the elasticities is apparent from Table 11 since the elasticities and cross-elasticities are different to those obtained for leisure travel despite the business and the leisure samples having similar underlying market shares (after adjusting the mode specific constants).

Table 11: Business Choice Elasticities

η^{C}_{CC}	η^{C}_{TC}	η^{T}_{CT}	η^{T}_{TT}	η^{T}_{HT}	η^{T}_{IT}*	η^{T}_{CC}	η^{T}_{TC}	η^{C}_{CT}	η^{C}_{TT}	η^{C}_{HT}	η^{C}_{IT}*
-0.01	-0.05	-1.50	-1.46	-1.11	-25%	0.05 <u>0.03</u>	1.46 <u>0.95</u>	0.06 <u>0.02</u>	0.05 <u>0.02</u>	0.03 <u>0.01</u>	3% <u>1%</u>

Note: * The interchange 'elasticities' represent the effect on car or train demand of each person having an additional interchange on each leg of their journey. The underlined figures are adjusted for the proportion of travellers whose choice probabilities are unaffected by changes in the characteristics of the other mode.

The cross-elasticities are adjusted according to the proportion who would be affected by the changes in the characteristics of the other mode. Assuming that coach does not enter the choice set, that the relative shares of train and car are as in Table 1 and that the coach alternative proportions are split equally between train/car and no alternative, then 39% of car users are affected by changes to train and 65% of rail users are affected by changes to car.

The car cost elasticity is low. This is because 85% of respondents cited the car cost to be zero, with most of the remainder reporting what seems to be a parking charge. However, almost all reported a train cost. This findings would appear to be a function of the way in which the questions were asked, with the car cost question asking for a zero cost if the company met the costs of the trip. This not only means that the car cost elasticity will be low but that it is essentially meaningless as an indicator of the dependence of car demand on car cost. Similarly, since car cost enters the cross-elasticity of train demand with respect to car cost, the latter figure is meaningless. This is clear from Table 11 since we would expect this figure to be fairly high on the basis of rail's very small market share but in fact the estimated cross-elasticity is negligible. However, the main cost cross-elasticity of interest here is the cross-elasticity of car demand with respect to train cost and this is unaffected by reporting of zero car cost. Indeed, all the car cross-elasticities seem plausible given that we would expect to have greater difficulties enticing business travellers out of their cars than leisure travellers, particularly on the sort of cross-country train services in the data set here.

The train time cross-elasticity is higher than for leisure and is arguably implausibly high although the rail share is low. The car time elasticity appears low despite a car value of time which is consistent with other evidence.

The rail cost and time elasticities are both very high. Journey time elasticities for train of around -0.8 are considered reasonable whilst Owen and Phillips (1987) cite first class fare elasticities, where business travel dominates, of -1.00. The latter was based on London journeys, where the seniority of business travellers and the type of business trip being made may well differ from those in our sample. However, the high elasticities in Table 11 are quite clearly influenced by rail's low share; we would expect rail to capture more than 14% of those choosing between rail and car on London routes. The headway elasticity is again too high (we have discussed why this is so) and subsequent use of this model should involve a somewhat lower headway coefficient. The interchange elasticity seems reasonable and it is not surprising that it is higher than for leisure.

Table 12 shows how selected point elasticities vary across different circumstances in much the same way as was done for leisure travel and for the range of circumstances that were depicted in Table 6 with the exception that the car costs were set to zero. However, setting the car costs to zero has very little effect on the forecast market share.

Table 12: Selected Elasticities for Business Travel

Flow	Elasticities						
	η^{C}_{CC}	η^{T}_{CT}	η^{T}_{TT}	η^{T}_{HT}	η^{C}_{CT}	η^{C}_{TT}	P_C
Blackpool-Norwich	-0.00	-3.49	-1.51	-1.62	0.00	0.00	0.99
Manchester-Cardiff	-0.00	-2.64	-1.47	-0.79	0.03	0.01	0.97
Sunderland-Chester	-0.00	-2.90	-1.51	-1.63	0.00	0.00	0.99
Liverpool-Peterborough	-0.00	-2.52	-1.47	-0.79	0.03	0.01	0.97
Chester-Hull	-0.00	-2.28	-1.49	-0.80	0.01	0.01	0.98
Bradford-Leicester	-0.00	-1.73	-1.50	-0.80	0.01	0.01	0.99
Leeds-Chester	-0.00	-1.44	-1.44	-0.78	0.03	0.03	0.95
Manchester-York	-0.00	-0.90	-1.16	-0.31	0.10	0.14	0.76
Bradford-Sheffield	-0.00	-0.82	-1.41	-0.76	0.03	0.04	0.93
Leeds-Manchester	-0.00	-0.67	-1.10	-0.20	0.10	0.16	0.73

Note: The cross-elasticity terms have been adjusted to account for those who would not be affected by the change in travel characterstics.

The car cost elasticity is zero, because car cost is zero, whilst the train cost elasticity exhibits considerable variation, partly because cost itself varies a great deal and also because of the variation in market share. Whilst these train cost elasticities seem strange compared with the conventional wisdom, we must bear in mind the extreme market shares at which some of them are evaluated and that they only relate to a portion of the rail market. The time elasticity does not vary greatly, because of the form in which time enters the utility function, whilst the headway elasticity varies considerably as expected. The cross-elasticities are all very low which is not surprising given cars dominance in the market.

The main problem with the business travel model we have developed is apparent from the figures reported in Table 12. Firstly, the model predicts a higher rail share and higher cross-elasticities of car demand for shorter distance trips. We would expect the reverse to apply, that rail is a more attractive proposition for business travel as distance increases, because the effort involved in driving may well increase more than proportionately with distance and because of increased opportunities to undertake worthwhile amounts of work during the course of a train journey. Secondly, whilst we can accept the market share estimates as plausible for Trans-Pennine trips where rail is not particularly attractive, we would require the model to give a much larger share to rail for trips to London where rail performs much better. For example, rail has a very healthy share of the business market between Leeds and London. However, if we enter typical characteristics of this journey for rail and car, we find that rail has a very low share of only a few per cent. This is partly because the rail share tends to fall with distance, but also because of the much higher fares per mile paid by business travellers on London routes. It does not seem reasonable to argue that there is a large number of rail users who consider themselves to have no alternative thereby implying a more respectable overall rail share for business travel.

The results for the business model are clearly less satisfactory than for the leisure model. Although the car cross-elasticities appear plausible, and these are the most important figures for the purposes of this study, we must place serious reservations about the use of this model to forecast business travellers' mode choices even though there is little else to use if this is what we wish to forecast. In particular, we could not recommend its use for London based trips.

6. CONCLUSIONS

The research reported here has formed an extension of the analysis conducted by TPA (TPA, 1992a, 1992b) into the mode choice behaviour of long distance travellers. There have been very few studies of modal choice for long distance travel in Great Britain; the analysis reported here has focussed upon choices between car and train and is based on individuals' actual behaviour. We have extended the previous analysis by disaggregating by journey purpose, by distinguishing between group and solus travel and by maintaining the power function model.

Of particular concern has been our attempt to identify the appropriate functional form of the mode choice model, which determines the properties of the implied elasticities and relative valuations, rather than impose a particular form on the data. We have seen that this procedure allows appreciable improvement in fit despite the fact that the utility function does not differ greatly from the form that would have otherwise been imposed. The form of utility expression and hence elasticity function that has been examined has not seen widespread application in mode choice models.

The most striking finding with respect to functional form is that, for both leisure and business trips, travel time enters the utility expression in logarithmic form. This implies that the journey time elasticity is not very sensitive to the level of journey time since the elasticity will only vary with time through the effect of the latter on the probability. This contrasts with the conventional utility function which implies a very strong relationship between the time elasticity and the amount of journey time. It also implies that the value of time falls as journey time increases: for example, the value of a 5 minute time saving is more highly valued on a 1 hour journey than on a three hour journey.

Despite the fact that we allowed the cost elasticity variation to be dampened in relation to that implied by the conventional utility function, we found that large cost elasticity variation with respect to the level of cost is empirically supported. This was the case for the six cost coefficients estimated in the two models. We also found, in both the leisure and business models, that the effect of interchange was found to increase more than proportionately with the number of interchanges.

Estimating the effect of train headway on behaviour has been problematic. This is not uncommon with mode choice models based on actual behaviour and would seem to relate to the generally higher level of uncertainty that surrounds this variable, particularly amongst car users. Implausible elasticities were obtained in both models, and indeed the valuations of headway were not consistent with other published evidence. In the case of the business model, a large correlation with the mode specific constant would seem to be a contributory factor. We recommend that lower headway coefficients are used in subsequent forecasting applications, with a halving in the case of leisure travel.

Some interesting findings have emerged with regard to group and solus travel. It was found that the cost elasticity of those travelling in groups was more sensitive to cost variations than for those travelling alone; this is to be expected given the larger implied income effects for those in a group. The difference in the disutility attributable to cost, to which the lower cost per person for group travel will contribute, is such that, for a given set of circumstances, those travelling alone would have a somewhat higher chance of using rail and indeed it would be very difficult to attract group travellers from car to train. In order to make substantial inroads into group leisure travel by car, special initiatives would be required, along the lines of the railcards available for group travel in the South-East. Given the importance of this issue, and that the available data does not allow a more detailed analysis of group effects, we recommend that further research is conducted which specifically targets this issue.

There are also those who are 'captive' to car in the sense that they have no alternative mode of travel or at least would not consider using another mode of travel. Again more detailed research is required here since the data available to us only allows crude approximations to be made. Models are required which can predict the composition of the choice set, although clearly there is little point in developing models to explain the choices of travellers who would never use anything but car. In particular, more detail is required to establish the extent to which group travellers dominate the latter group. We note, however, that the combination of group travellers having a low propensity to choose rail and the large proportion (70%) of car users who are captive means that overall the degree of interaction between car and rail is very limited.

Three aspects of demand which can be examined by the models reported here are the modal shares of train and car, the own elasticities of train and car and the cross-elasticity effects of train and car. We now draw our conclusions regarding the business and leisure models in terms of these three aspects.

Cross-Elasticities

This is the most important issue as far as this study is concerned, particularly the forecasting of the extent to which car demand can be reduced as a result of improvements to train. The major problem here, although not unique to this study, is that the degree of switching between modes depends on what proportion of the rail and car markets are taken to be 'captive' to that mode given that it cannot be possible to develop revealed preference models that contain people who, for whatever reason, would never consider using another mode. That there are such travellers, particularly car users, cannot be doubted.

With regard to leisure travel, we believe that, with the exception of the headway cross-elasticity, the car and train cross-elasticities are reliable and can be used to predict mode switching. We recommend that the headway coefficient is reduced by half to be more consistent with other evidence and this would provide a more plausible headway cross-elasticity.

Although there are deficiencies in the business model, the cross-elasticities of car demand with respect to characteristics of train appear reasonable, and as might be expected are lower than for leisure travel. However, the headway coefficient requires adjustment to correct for what we believe to be a too high headway coefficient and we recommend the same adjustment as for leisure travel. The train cost cross-elasticity is meaningless, because car cost is effectively zero, and the train time elasticity seems too high. Whilst we can recommend the cross-elasticities for forecasting the effect on car demand, which is of greatest interest to us, we could not do so for predicting the effect of car on train demand. However, the car cross elasticities may be too low for London routes since the model would under-predict rail's share on these routes.

Own-Elasticities

The leisure own elasticities, after adjusting the headway coefficient, are acceptable for both car and train. For business travel, the car own cost elasticity cannot be derived from the model and the time elasticity appears suspect. The rail business elasticities are too high.

A limitation here is that the mode choice elasticity only tells us part of the story since there is also the portion of the market who are choosing between rail/car and either coach or not travel at all. We either need a model for these portions of the market or else need to make assumptions about the elasticities in these market segments relative to the one we have estimated.

Market Share

We recommend the use of the leisure model to predict market share amongst those choosing between train and car, although we note the problem, as discussed above, relating to the segmentation of the market according to choice set. However, we cannot recommend the use of the business model to forecast market share since rail's share falls with distance and we find this to be quite undesirable, whilst it could not reflect the attractiveness of rail on London routes. Moreover, our sample of business travellers may well be somewhat different in terms of seniority and purpose of their business trip than on London flows.

This paper has been technical in nature, concentrating on modelling issues and aiming to obtain models which provide the best explanation of mode choice behaviour. Subsequent papers will address the following issues:

i) Comparison of the cross-elasticities with those from other studies. Whilst there have been few other studies, two recent examples are a study conducted for the Department of Transport which examined the interaction between the M1 and A1 routes and parallel rail routes and a study conducted for the Scottish Office which examined mode choice behaviour for journeys across the Firth of Forth.

ii) Comparison with the aggregate models developed as part of this overall study into inter-modal interactions.

iii) The assessment of estimated own and cross-elasticities in terms of the relationships apparent in conventional economic theory.

iv) The use of the models to forecast the impact of various rail improvements on the demand for car travel and the evaluation of alternative scenarios for reducing car demand.

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