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DISAGGREGATE URBAN MODE CHOICE MODELS:

A Review of British Evidence with Special Reference to Cross Elasticities

M WARDMAN

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1. OBJECTIVES

As part of an EPSRC funded research project (GRK52522) entitled 'National Multi-Modal Travel Forecasts', a review of the demand forecasting literature has been conducted. The principal aim of this project is to develop a set of national and regional travel demand forecasts by land-based modes. Such models will contain a set of own and cross-elasticities which can be used in strategic demand forecasting. A review of the literature, alongside fresh empirical work, makes an important contribution to this.

A review of aggregate models is contained in Clark (1996). Such models are based on collective behaviour such as market shares or travel volumes. In contrast, disaggregate models make the individual decision maker the unit of observation. Within this project, Wardman (1997a) has provided a review of disaggregate mode choice models developed in the inter-urban context in Great Britain whilst Whelan (1997) has provided a review of car ownership modelling and forecasting.

This paper provides a review of comparatively recent research involving disaggregate mode choice models which have been developed in Great Britain in the urban context. The emphasis of this research is on cross elasticities for three reasons:

i) Mode choice models are well suited to the estimation of cross-elasticities;

ii) The own elasticities provided by disaggregate mode choice models are underestimates since they do not account for behavioural responses other than mode switching (Oum et al., 1992);

iii) There has long been a view (Dodgson, 1991) that there is insufficient evidence regarding the degree of interaction between modes and this view remains (Acutt and Dodgson, 1995; Wardman et al., 1997)

In contrast, aggregate models are well suited to the analysis of own elasticities since they take into account changes in the total number of trips yet they are generally limited in the extent to which they examine inter-modal competition and hence generally provide little evidence on cross-elasticities.

In this paper, we have drawn upon studies made available to us as part of a review study conducted for the Department of Transport into the value of time (Wardman, 1997b). Much of this evidence was provided on the basis that the identity of the studies remains anonymous. We have therefore provided the key parameter estimates from 34 studies without revealing the identity of these studies. We have included studies concerned with light rapid transit but these have been indicated in the text.

The review of inter-urban evidence (Wardman, 1997a) argued that any multi-modal forecasting procedure ought to ensure that the own and cross elasticities are consistent with each other and with theory. Standard choice models, such as the multinomial and hierarchical logit models, do not ensure that all such properties are satisfied; for example, the sum of the own and cross fare elasticities will only equal zero in a special set of circumstances. In addition to checking the consistency of elasticities, various formulae are available which can be used to deduce unknown elasticities from other available empirical evidence (Toner, 1994). Whilst we have not repeated the discussion of these issues in this paper, we do regard them to be of equal importance to the analysis of interactions between modes in the urban context. Nor have we repeated the discussion of the elasticity properties of choice models contained in the accompanying paper dealing with inter-urban models.

We also showed in the review of the inter-urban literature that the cross elasticities, which are the focus of this paper, can be expected to vary across different circumstances and particularly to be sensitive to modal share. This means that the cross-elasticity estimates quoted in a particular study might be highly specific to that context and therefore we must be careful to avoid generalising from specific situations.

There are two noticeable, and not unrelated, features of the findings we present here for the urban context. Firstly, all the studies are based on Stated Preference (SP) data. In the inter-urban context, recent studies have involved both Revealed Preference (RP) and SP modelling exercises. In contrast, SP models dominate in the urban and suburban context. The RP models that were available to us were either dated, for example, the mode choice models reported in MVA (1983), Preston (1987) and WMCC (1984) were based on data collected in the early 1980's, or else contained few observations (TPA and ITS, 1990), were commercially confidential or examined choice contexts which do not provide cross elasticities between modes (Hague Consulting Group and Accent, 1996). Secondly, we do not have any recent models which examine choices between all three main modes simultaneously. In part this is because we do not have RP studies but the principal factor here is that it is rare for SP models to include more than two modes.

In almost all cases, the reports do not provide cross-elasticity estimates, although we have stated that these will be very context specific. In part, this is because many studies examined a situation where one mode did not exist, such as studies of new stations, guided bus or LRT schemes, and thus cross-elasticities cannot be calculated for the base situation. In other studies, the main emphasis was on estimating relative valuations rather than elasticities. We have therefore calculated cross-elasticities for a range of situations which we regard to be representative of urban travel conditions. For reasons already discussed, we have not used the models to estimate own elasticities.

The layout of this paper is as follows. Section 2 provides the empirical evidence in terms of the coefficient estimates of the studies available to us. These models are binary choice logit models, and we have separated the results according to whether the models examine choices between rail and car, between rail and bus or between car and bus. Section 3 presents cross-elasticity estimates for each set of models for a range of situations. The problems of applying the results are discussed in section 4 whist section 5 considers an alternative approach to the estimation of cross elasticities. Concluding remarks are contained in section 6.

2. THE EMPIRICAL EVIDENCE

Unlike the inter-urban context where there are sufficiently few disaggregate mode choice models that each can be individually discussed in some detail, there are too many urban studies to review in such detail. We therefore simply present the coefficient estimates for each study which can be used to calculate market share forecasts and elasticities.

We report coefficient estimates for mode choice models specified primarily in terms of time, cost, walk time and headway for rail and car models, rail and bus models and car and bus models. In each case, we provide information on the following factors:

i) Date

This is the date when the data was collected.

ii) Study

This is a number which, for our purposes only, identifies the study should it subsequently need to be identified. It also denotes, in brackets, whether the data was collected from only a sub-sample of the modes to which the model relates. (C), (T) and (B) therefore denote respectively that the model was estimated on just car, train or bus users.

iii) Constant

This is the mode specific constant (MSC). It is specified in favour of rail where rail is present and in favour of car for the car and bus choice models.

iv) Headway, Walk, Time, Cost and Other Coefficients

These are presented in pence and minutes for a one-way journey. Generally, no distinction is made in the coefficients by mode. However, separate values are given where mode specific parameters have been estimated. Where another coefficient is specified (Other), we denote what the variable is. We have not presented the t statistics but an asterisk denotes that a coefficient is not significant at the usual 5% level. The coefficients relate to a linear-additive utility function except for piecewise coefficients which are explained in the notes to the tables.

v) Observations

This denotes the number of observations upon which the model is calibrated.

vi) Context

This denotes whether the journey purpose is commuting or leisure or indeed whether no distinction (No Dist) is made. We also distinguish peak and off-peak trips since some studies use this dimension to segment the data. Whilst some of the no distinction category, and indeed some within the peak and off-peak categories, may have been making business trips, in these urban studies the proportions of such travellers are likely to be very small.

2.1 Rail and Car Models

Table 1: Rail and Car Binary Choice Logit Models

Date	Study	MSC	Head	Walk	Time	Cost	Other	Obs	Context
89	1(C)	-0.531•	F5=0.44 F20=-0.84 F10=0.0	-0.098	-0.085	-0.039		816	Peak
89	1(C)	-0.798•	F5=0.23 F20=-0.74 F10=0.0	-0.083	-0.063	-0.022		1812	Off Peak
93	2(C)	-0.068•	-0.030	-0.077	-0.039	-0.028		1216	Peak
93	2(C)	0.336•	-0.039	-0.083	-0.048	-0.026		1456	Off Peak
	3(C)	0.295	F15=1.11 F20=1.07 F30=0.54 F60=0.0	-0.122	-0.091 -0.047	-0.017		892	No Dist
93	4(C)	0.0*	-0.037	-0.064	-0.099	-0.028		442	Comm
93	4(C)	0.0*	-0.023	-0.047	-0.037	-0.020		1377	Leis
92	5(C)	0.372	n/a	-0.120	-0.083 -0.073	-0.016		1242	No Dist
88	8(C)	-0.746	0.948[1]	-0.080	-0.071	-0.038		2160	No Dist
89	9(C)	-0.224•	0.116[1]	-0.234	-0.087	-0.038		1743	No Dist
92	10(C)	0.0*	-0.017	-0.044	-0.036 -0.042	-0.010		9034	No Dist
90	12(C)	-0.460•	-0.035	-0.030	-0.120	-0.023		1323	No Dist
91	13(C)	-0.354•	-0.031	-0.022	-0.023	-0.005		3591	Peak
91	13(C)	-0.155•	-0.018	-0.020	-0.007	-0.006	-0.554[2]	2274	Off Peak
92	14(C)	-0.353•	-0.032	n/a	-0.044	-0.029		848	Peak
92	14(C)	0.454•	-0.055	n/a	-0.080	-0.032		1704	Off Peak
93	15(C)	0.0•*	n/a	-0.051	-0.114 -0.084	-0.064		2871	No Dist
95	16(C)	-0.672•	-0.048[3]	-0.033	-0.035	-0.007	-0.260[4]	1296	No Dist
87	17(C)	-1.907	1.451[1]	-0.082 -0.039	-0.064	-0.035		4314	No Dist
96	18(T)	0.981	n/a	n/a	-0.035	-0.018	-0.022[5]	1485	Comm
96	18(C)	0.806	-0.056	n/a	-0.046	-0.020		1809	Leis
89	19(C)	-0.321	-0.012	-0.037	-0.021	-0.017		2492	Comm
89	19(C)	-0.750	-0.012	-0.037	-0.021	-0.017		2492	Leis

89	20(C)	-0.976	-0.022	-0.059	-0.029	-0.011		2090	Comm
89	20(C)	-1.421	-0.022	-0.059	-0.029	-0.011		2090	Leis

Table 1 (cont)

Date	Study	MSC	Head	Walk	Time	Cost	Other	Obs	Context
90	21(C)	0.460•	-0.088[3]	-0.069	-0.043 -0.052	-0.024		736	Peak
90	21(C)	-0.655•	-0.052[3]	-0.066	-0.058 -0.023	-0.024		1408	Off Peak
91	22(C)	0.109•*	-0.093	-0.038	-0.058	-0.016		927	Peak
91	22(C)	-0.213•	-0.015*	-0.064	-0.027	-0.015		936	Off Peak
90	23(C)	0.0*	F5=0.0 F10=-0.43 F15=-0.64 F30=-1.84	-0.100	-0.077 -0.063	-0.019 -0.024	-0.817[2]	1779	Comm
89	24(C)	0.0*	-0.043[3]	-0.086	-0.042	-0.019	-0.571[2]	2210	Comm
91	25(C)	-1.336	n/a	-0.032	-0.031	-0.019		1323	No Dist
92	27(C)	0.529•*	-0.031	-0.074	-0.061	-0.008		336	Peak
92	27(C)	0.768•*	-0.077	-0.099	-0.094	-0.030		621	Off Peak
89	28(C)	-0.215	-0.006	-0.070	-0.035	-0.012		640	Peak
89	28(C)	-0.169	-0.006	-0.084	-0.042	-0.013		702	Off Peak
92	29(C)	0.549•	-0.028	-0.059	-0.035 -0.029	-0.025		827	No Dist
88	30(C)	0.518•	-0.044[3]	-0.044	-0.032 -0.006	-0.004		5247	Leis
88	30(C)	-1.783	n/a	n/a	-0.031 -0.038	-0.047 -0.009		1251	No Dist
92	31(C)	-1.191	n/a	n/a	-0.004	-0.004		513	Comm
90	32(C)	0.0*	n/a	-0.135	-0.062	-0.016		329	Peak
90	32(C)	0.0*	n/a	-0.184	-0.091	-0.018		350	Off Peak
91	33(C)	-0.663	-0.033	-0.127	-0.059	-0.022		1743	No Dist
91	34(C)	0.0*	-0.017	n/a	-0.022	-0.006		651	Comm

Notes to Table 1. 1 = Services per hour, 2 = Interchange, 3 = Wait Time, 4 = Parking Restricted, 5 = Parking cost. * denotes not statistically significant at the 5% level and • denots that the constant term relates to light rapid transit. Where two figures are given in a cell, the first relates to train and the second to car. Otherwise the same coefficient applies to each mode. Piecewise estimation was used in some studies to estimate the effects of different frequency levels. These are denote by F in the headway column along with the service interval to which the coefficient relates. The base category is denoted with a zero coefficient. Thus for study 3, F20 denotes that the coefficient for a 20 minute interval is 1.07 and this is interpreted in relation to a base category of an hourly interval.

2.2 Rail and Bus Models

Table 2: Rail and Bus Binary Choice Logit Models

Date	Study	MSC	Head	Walk	Time	Cost	Other	Obs	Context
	3(B)	0.732*	-0.018*	-0.072	-0.072	-0.032		507	No Dist
93	4(B)	1.012	-0.027	-0.101	-0.045	-0.033		418	Comm
93	4(B)	0.0	-0.022	-0.033	-0.028	-0.032		1136	Leis
92	7(B)	-0.237	-0.039	-0.096	-0.051	-0.014	-0.204[1]	3015	No Dist
88	8(B)	0.166	0.723[2]	-0.077	-0.065	-0.074		4688	No Dist
89	9(B)	0.598•	0.069[2]	-0.170	-0.061	-0.073		2816	No Dist
92	10(B)	0.0	-0.028 -0.022	-0.115	-0.057 -0.056	-0.035		3877	No Dist
90	12(B)	0.880•	-0.050	-0.100	-0.049	-0.037	-1.902[1]	1242	No Dist
91	13(B)	-0.215•	-0.035	-0.092	-0.044	-0.017	-0.789[1]	706	Peak
91	13(B)	0.857•	-0.079	-0.054	-0.025	-0.043	-0.684[1]	708	Off-Peak
87	17(B)	0.0	1.324[2] 0.862[2]	-0.067	-0.086	-0.056		2549	No Dist
89	19(B)	-1.398	-0.012	-0.051	-0.025	-0.018		2700	Comm
89	19(B)	-0.667	-0.012	-0.051	-0.025	-0.018		2700	Leis
89	20(B)	0.207	-0.033	-0.063	-0.037	-0.021		1158	Comm
89	20(B)	0.207	-0.049	-0.095	-0.055	-0.032		772	Leis
90	23(B)	2.082	F5=0.0 F15=-0.75 F30=-2.51	-0.139 -0.104	-0.063 -0.076	-0.028		804	Comm
89	28(B)	0.294	-0.007	-0.053	-0.027	-0.020		602	Peak
89	28(B)	0.282	-0.006	-0.050	-0.025	-0.021		563	Off Peak

Notes to Table 2. 1 = Interchange, 2 = Services per hour. Where two figures are given in a cell, the first relates to train and the second to bus. Otherwise the same coefficient applies to each mode. Piecewise estimation was used in some studies to estimate the effects of different frequency levels. The other notation is as for Table 1.

2.3 Car and Bus Models

Table 3: Car and Bus Binary Choice Logit Model

Date	Study	MSC	Head	Walk	Time	Cost	Other	Obs	Context
93	2(C)	-0.040	-0.040	-0.086	-0.055	-0.023		1427	Peak
93	2(C)	-1.228	-0.057	-0.152	-0.058	-0.023		1168	Off Peak
90	6(C)	-0.741	-0.048	-0.120 -0.097	-0.057 -0.015	-0.004 -0.024		1639	No Dist
92	7(C)	-0.771	-0.031	-0.074	-0.041	-0.010		4004	No Dist
94	11(C)	-0.040*	-0.022*	-0.028	-0.007*	-0.012	0.195[1]	603	Comm
94	11(C)	0.558	-0.069	-0.018	-0.017*	-0.011		1602	Leis
92	14(C)	0.571	0.0*	-0.034	-0.034	-0.018		872	Peak
92	14(C)	0.249	-0.040	-0.031	-0.031	-0.021		1760	Off Peak
95	16(C)	0.824	-0.073	0.0*	-0.035	-0.017	-1.005[2]	1768	Peak
95	16(C)	1.437	-0.069	-0.030	-0.030	-0.007	-0.204[2]	1867	Off Peak
93	26(C)	-0.584*	-0.027[3]	-0.027	-0.027	-0.005 -0.004		549	Comm
93	26(C)	-0.521*	-0.032[3]	-0.032	-0.021	-0.008 -0.004		873	Leis
92	29(C)	0.509	-0.028	-0.059	-0.029 -0.043	-0.025		827	No Dist
91	33(C)	0.0*	-0.095	-0.156	-0.071	-0.024		2121	No Dist
91	34(C)	0.0*	-0.046	-0.046	-0.046	-0.011		504	Comm

Notes to Table 3. 1 = Distance (miles) specific to car, 2 = Parking restricted, 3 = Wait time. Where two figures are given in a cell, the first relates to car and the second to bus. Otherwise the same coefficient applies to each mode. The other notation is as for Table 1.

3. CROSS ELASTICITIES

We now use the models reported in Tables 1-3 above to calculate cross elasticities. In all cases, we will distinguish between:

- shorter, essentially urban, journeys of around 2 miles
- longer, essentially suburban, journeys of around 10 miles.

The characteristics of car are varied little across the scenarios considered. However, we do specify somewhat different levels of attractiveness of the public transport options so as to be able to examine the sensitivity of the cross elasticity estimates to the market share position.

We will use the following equation to calculate arc cross elasticities:

$$\eta_{ik}^{\text{arc}} = \frac{\log \frac{P_{i2}}{P_{i1}}}{\log \frac{X_{k2}}{X_{k1}}} \qquad (1)$$

where P_i denotes the market share of alternative i, X_k represents the level of some variable on alternative k and 1 and 2 denote the before and after periods. The formula effectively estimates a constant elasticity between two points which is the same measure in both directions and has the same properties as the point elasticity.

3.1 RAIL AND CAR

3.1.1 Rail and Car Scenarios

Table 4 lists a series of situations for train and car for the two journey lengths. No distinction is made between peak and off-peak characteristics but peak and off-peak forecasts of train market share ($Share_T$) are provided in the final two columns using the peak/commuting models and off-peak/leisure models. We have assumed petrol costs of £2.50 per gallon and fuel consumption of 20 miles per gallon for 2 mile trips and 30 miles per gallon for 10 mile trips. Parking is assumed to be 50 pence, which is relatively low but attempts to take into account that some have free parking, and it is divided by two to be in single trip units.

Table 4: Car and Rail Scenarios and Rail Market Share

	Miles	$Head_T$	$Walk_T$	$Walk_C$	$Time_T$	$Time_C$	$Cost_T$	$Cost_C$	Peak $Share_T$	Off-Peak $Share_T$
1	2	10	10	2	5	8	40	50	0.39	0.38
2	2	10	20	2	5	8	40	50	0.28	0.27
3	2	30	10	2	5	8	70	50	0.20	0.17
4	2	30	20	2	5	8	70	50	0.15	0.11
5	10	10	10	2	15	25	80	108	0.54	0.51
6	10	10	20	2	15	25	80	108	0.41	0.37
7	10	30	10	2	15	25	150	108	0.19	0.15
8	10	30	20	2	15	25	150	108	0.14	0.10

It can be seen that, as would be expected, the majority of trips would be by car in such circumstances. It can also be seen that there is considerable variation in market share. The rail share is greater for the longer distance trips because here the penalties associated with walk time and headway form a smaller proportion of generalised cost. However, the figures contained in Table 4 relate to a corridor where rail is present. For many urban journeys the probability of using rail will be negligible since rail services are not accessible.

3.1.2 Rail and Car Cross Elasticities

Table 5 and 6 provide cross elasticity estimates for the peak and off-peak models respectively. The elasticities vary considerably with market share and the large cross-elasticities of rail demand with respect to car journey times and costs reflect the relatively low rail market share. The cross elasticities of rail demand with respect to car characteristics are generally far higher than have been observed in the literature although the cross elasticities of car demand with respect to rail characteristics seem more plausible. However, the cross elasticities with respect to car characteristics would be even higher and the cross elasticities with respect to rail characteristics lower if allowance was made for the sparcity of the rail network given the effect that the latter would have on relative market shares.

Table 5: Rail and Car Peak Cross Elasticities

Scenario	$Cost_T$ -10%	$Time_T$ -10%	$Head_T$ -50%	$Cost_C$ -10%	$Time_C$ -10%

1	0.25	0.08	0.07	0.50	0.20
2	0.17	0.05	0.05	0.53	0.21
3	0.18	0.03	0.10	0.50	0.21
4	0.12	0.02	0.06	0.47	0.19
5	0.66	0.33	0.09	0.82	0.47
6	0.52	0.25	0.07	1.01	0.59
7	0.39	0.10	0.10	1.06	0.68
8	0.25	0.06	0.06	0.99	0.61

Table 6: Rail and Car Off Peak Cross Elasticities

Scenario	$Cost_T$ -10%	$Time_T$ -10%	$Head_T$ -50%	$Cost_C$ -10%	$Time_C$ -10%
1	0.25	0.08	0.07	0.52	0.19
2	0.16	0.05	0.05	0.55	0.20
3	0.19	0.03	0.12	0.62	0.23
4	0.12	0.02	0.08	0.63	0.22
5	0.61	0.30	0.08	0.83	0.45
6	0.44	0.20	0.06	0.99	0.52
7	0.38	0.09	0.10	1.34	0.76
8	0.25	0.06	0.07	1.38	0.82

3.2 RAIL AND BUS

3.2.1 Rail and Bus Scenarios

Table 7 presents the scenarios we have considered for competition between rail and bus and also provides the train market share estimates obtained from application of the models. Train achieves the greater share in all circumstances where it is cheaper and again there is considerable variation in market shares across the set of scenarios examined. However, there remains the issue of the unavailability of rail services for many urban journeys; the rail shares in Table 7 are appropriate for a corridor where rail is present but would be somewhat lower if considering shorter distance journeys in general.

Table 7: Rail and Bus Scenarios and Rail Market Share

	Miles	$Head_T$	$Head_B$	$Walk_T$	$Walk_B$	$Time_T$	$Time_B$	$Cost_T$	$Cost_B$	Peak $Share_T$	Off-Peak $Share_T$
1	2	10	10	10	5	5	10	40	50	0.57	0.57
2	2	10	30	20	15	5	10	40	50	0.68	0.69
3	2	30	10	20	5	5	10	70	50	0.15	0.16
4	2	30	30	10	15	5	10	70	50	0.59	0.50
5	10	10	10	10	5	15	30	80	100	0.68	0.70
6	10	10	30	20	15	15	30	80	100	0.76	0.78
7	10	30	10	20	5	15	30	150	100	0.12	0.10
8	10	30	30	10	15	15	30	150	100	0.53	0.37

3.2.2 Rail and Bus Cross Elasticities

Tables 8 and 9 provide the cross elasticity estimates between rail and bus for peak and off-peak travel. Again some large variations with market share are observed; for example, the cross elasticity with respect to bus cost is very high when rail's share is relatively low in scenarios 3 and 7 whilst the cross elasticity with respect to train cost is large in scenario 6 where the rail share is relatively large. The cross elasticities would also be affected by somewhat lower rail shares for urban journeys in general rather than for situations where there is an accessible rail service and this would tend to make the rail cross elasticities larger and the bus cross elasticities lower.

Whilst rail and coach are generally regarded to be reasonably close substitutes and to compete in the same market of non car owning travellers, the cross elasticities do tend to be higher than we had expected.

Table 8: Rail and Bus Peak Cross Elasticities

Scenario	$Cost_T$ -10%	$Time_T$ -10%	$Head_T$ -50%	$Cost_B$ -10%	$Time_B$ -10%	$Head_B$ -50%
1	0.39	0.08	0.09	0.38	0.13	0.07
2	0.41	0.09	0.09	0.27	0.09	0.16
3	0.23	0.03	0.12	0.91	0.31	0.14
4	0.71	0.09	0.28	0.36	0.13	0.26
5	0.86	0.28	0.09	0.53	0.27	0.05
6	0.89	0.28	0.09	0.38	0.19	0.10
7	0.43	0.06	0.10	1.89	1.00	0.15
8	1.44	0.24	0.26	0.85	0.44	0.29

Table 9: Rail and Bus Off-Peak Cross Elasticities

Scenario	$Cost_T$ -10%	$Time_T$ -10%	$Head_T$ -50%	$Cost_B$ -10%	$Time_B$ -10%	$Head_B$ -50%
1	0.59	0.08	0.12	0.57	0.12	0.10
2	0.59	0.09	0.10	0.35	0.08	0.18
3	0.29	0.02	0.11	1.05	0.22	0.14
4	0.97	0.07	0.35	0.70	0.15	0.40
5	1.34	0.28	0.12	0.80	0.25	0.06
6	1.26	0.28	0.09	0.49	0.16	0.11
7	0.43	0.04	0.06	2.08	0.70	0.12
8	1.68	0.16	0.30	1.77	0.57	0.45

3.3 CAR AND BUS

3.3.1 Car and Bus Scenarios

The car and bus scenarios are presented in Table 10. Again we assume a petrol cost of £2.50 per gallon and fuel consumption of 20 miles per gallon for 2 mile trips and 30 miles per gallon for 10 mile trips. Parking is assumed to be 50 pence and is divided by two to be in single trip units. As would be expected, car dominates in most instances but not to the extent that occurs in practice. In section 5, we quote relative shares of car and bus for the journey to work in urban areas of 84% and 14%. Thus scenarios 3, 4, 7 and 8 would seem to be most representative of actual urban conditions.

Table 10: Car and Bus Scenarios and Bus Market Share

	Miles	$Head_B$	$Walk_B$	$Walk_C$	$Time_B$	$Time_C$	$Cost_B$	$Cost_C$	Peak $Share_B$	Off-Peak $Share_B$
1	2	5	10	2	10	8	50	50	0.36	0.35
2	2	15	20	2	10	8	50	50	0.28	0.24
3	2	5	10	2	10	8	70	50	0.22	0.17
4	2	15	20	2	10	8	70	50	0.17	0.12
5	10	5	10	2	30	25	90	108	0.39	0.39
6	10	15	20	2	30	25	90	108	0.30	0.28
7	10	5	10	2	30	25	120	108	0.22	0.19
8	10	15	20	2	30	25	120	108	0.17	0.14

3.3.2 Car and Bus Cross Elasticities

Tables 11 and 12 contain the cross elasticities between car and bus for the range of situations presented in Table 10 for the peak and off-peak models. The high degree of variation in cross elasticities across different sets of market conditions that we have come to expect from the previous models is also apparent here.

There is an element of plausibility about the cross elasticities of bus demand with respect to the characteristics of car for the shorter distance journeys although these cross elasticities do seem to be large for the longer journeys. The cross elasticities of car demand with respect to bus costs are fairly plausible, and indeed the low market shares of bus will have contributed to these low elasticities. However, the elasticities do seem to be a little on the high side for the longer distance journeys.

Table 11: Car and Bus Peak Cross Elasticities

Scenario	$Cost_B$	$Time_B$	$Head_B$	$Cost_C$	$Time_C$

	-10%	-10%	-50%	-10%	-10%
1	0.22	0.11	0.07	0.39	0.15
2	0.16	0.08	0.05	0.41	0.16
3	0.16	0.06	0.11	0.40	0.15
4	0.12	0.04	0.08	0.40	0.15
5	0.46	0.36	0.08	0.83	0.45
6	0.33	0.27	0.06	0.88	0.48
7	0.29	0.17	0.12	0.87	0.48
8	0.21	0.12	0.08	0.85	0.47

Table 12: Car and Bus Off Peak Cross Elasticities

Scenario	$Cost_B$ -10%	$Time_B$ -10%	$Head_B$ -50%	$Cost_C$ -10%	$Time_C$ -10%
1	0.20	0.09	0.11	0.40	0.14
2	0.14	0.06	0.07	0.45	0.15
3	0.12	0.04	0.15	0.44	0.16
4	0.07	0.02	0.09	0.40	0.14
5	0.40	0.30	0.12	0.81	0.40
6	0.29	0.22	0.09	0.94	0.46
7	0.23	0.14	0.16	0.91	0.47
8	0.13	0.08	0.10	0.88	0.41

4. PROBLEMS APPLYING CHOICE MODELS TO STRATEGIC FORECASTING

There are a number of problems involved in using the evidence regarding cross elasticities which is provided by disaggregate choice models in strategic forecasting. We shall discuss each of these issues in turn.

4.1 Cross Elasticity Variation

The studies that we have reviewed place little emphasis on calculating cross elasticities and in any event they would be highly context specific. What is clear from our application of the choice models available to us is that there is considerable variation in cross elasticities according to the market position. The reasons for this can be clearly seen by reference to the logit model's point cross elasticity function.

Given a linear-additive utility function, which is the case for time and cost in all the choice models reported in Tables 1-3, and a binary logit formulation, the point cross elasticity of demand for mode i with respect to the level of some variable X on mode j (η_j) is calculated as:

$$\eta^{i}_{xj} = -\alpha_j X_j P_j \qquad (2)$$

Given that α_j will be negative, equation 2 will have the required positive sign. The sensitivity of the cross elasticity to the market share of alternative k (P_j) is immediately apparent. Indeed, equation 3 below which indicates the relationship between own and cross elasticities also shows how the cross elasticity is dependent on market share.

In addition, equation 2 shows the dependence of the cross elasticity on the level of the variable in question. Although the effect of increases in X_j on the cross elasticity will be dampened by the impact of X_j on P_j, it remains that for any given P_j a cross elasticity will be twice as large where X_j is twice as large. This is a shortcoming of the form of logit model that is conventionally developed if such large elasticity variation is not empirically justified.

The problem faced here in applying models which have been developed and applied to specific contexts is one of selecting the appropriate set of cross elasticities to apply at a regional or national level given the inherent level of variation in the cross elasticities. Selecting some average set of travel characteristics upon which to base the forecasts would not seem to be a particularly good way forward unless the characteristics were chosen so that the resulting market shares strongly ressembled actual market shares for the level of aggregation at which we wished to operate. Even then, the cross elasticities with respect to a particular variable will depend on the value assigned to the level of that variable.

Some of these problems would be avoided by applying the models in an incremental fashion. This has the advantage of being based on the average market share position and of not needing to specify base levels of variables since the model operates in terms of differences in utilities. If forecasts of the general effect of a reduction in bus fares were required then some average of the bus fare coefficients would be used. The problem with this approach is that the avoidance of the need to specify base values of the variables means that we cannot specify proportionate changes in the variables.

Whilst variation in elasticities is a problem in deciding which particular value to use, it would seem to be sensible to assess any cross elasticities derived by other means, and we shall discuss one such procedure below, by the extent to which they lie within the range of cross elasticities implied by application of the above models across an appropriate set of circumstances.

4.2 Degree of Interaction

Even if the cross elasticities implied by disaggregate mode choice models exhibited a much greater degree of stability across different circumstances, there would still be problems in applying the results derived from the models. There is a tendency for the cross elasticities reported above to be rather high. Table 13 contains the cross price elasticities cited by Toner (1993) in his review of urban demand elasticities. Comparison of these with the values obtained by the disaggregate choice models across a range of circumstances does indeed reveal that there is a tendency for the latter to be too high, particularly for the longer distance urban journeys. We shall also see in section 5 that an alternative means of calculating the cross elasticities also suggests that the cross elasticities obtained from the disaggregate mode choice models are too high. Similarly, the market share forecasts are in some cases inaccurate. For example, the choice models forecast a bus share amongst bus and car of 20-30% when in practice bus has less than 20% and this will impact on the cross elasticity estimates. In addition, train is estimated to gain what seems to be a too large share of those choosing between train and car.

Table 13: Urban Cross Price Elasticities in Toner (1993) Review

	Car Demand	Rail Demand	Bus Demand
Car Cost	-	0.34	0.62
Rail Cost	0.10	-	0.10
Bus Cost	0.10	0.20	-

There are two important issues which have a bearing on the magnitude of the cross elasticities obtained from disaggregate choice models; one relates to the extent to which individuals do actually make choices between different modes of transport and the other relates to what has been termed the scale factor problem. Failing to account for the former will lead to the cross elasticities being too high, which here appears to be a problem. The latter will impact on the cross elasticities but it does not necessarily increase them.

4.2.1 Choice Set Composition

In the forecasts above, bus is in many instances seen to be more sensitive to car than it is to train. Given our forecasts are based on the assumption of an effective train service, we would expect bus demand to be more sensitive to changes in train fare and service quality than to corresponding changes for car. This problem might not arise if our models allowed for the fact that some car users would never consider travelling by bus. This correction might also overcome what seems to be an overprediction of bus market share amongst those choosing between car and bus.

The models that have been used here tend to be calibrated to data supplied by those who consider themselves to have a real choice. For example, those who would not consider, say, public transport alternatives could have been removed from the modelling exercise, might have refused to answer any questions or indeed might not have been recruited in the first place. The estimated model therefore contains those with a larger than average propensity to switch modes. Yet the application of these models has not allowed for this. The problem in applying some adjustment to the cross elasticities to allow, for example, for public transport users who do not have a car available or car users who would never consider using public transport, is one of distinguishing between the extent to which alternatives are not considered because of personal preferences on the one hand and travel and personal circumstances on the other. Even if the proportion who do not have certain modes in the choice set is fairly constant across different circumstances, because say it is purely a matter of personal preferences rather than travel characteristics, there is still the problem of the lack of information on what this proportion is.

Hence a serious problem facing the use of disaggregate choice models to derive cross elasticities, even if these are to be highly specific to a particular set of travel conditions, is that there is a need to adjust for those whose cross elasticities are zero yet it is not clear what the adjustment is.

4.2.2 Scale Factor

The coefficients (α) of a discrete choice model are inversely related to the standard deviation of the error term that accounts for the net effect of omitted factors. If the standard deviation of the error term is too large, the coefficients will be too small and the forecasts will tend to their equal share values. Thus in these circumstances the share of the major mode will be underpredicted and the share of the minor mode will be overpredicted. This is termed the scale factor problem. It can occur in SP models, because responses contain a variety of possible errors not related to actual decision making, and it can occur in RP models, where there is misreporting of the attributes.

It can be seen from equation 3 that there will be an influence on the cross elasticities from the impact of the scale factor problem through both the coefficient estimates and the probabilities. Assuming that the error standard deviations in the SP models reviewed here are too large, as is expected to be the case, cross elasticities for the demand for minor modes will be too low since both α_j and P_j (the major mode) in equation 3 will be too low. This is alarming since, for example, the bus cross elasticities with respect to car attributes are already high. For minor modes, α_j is too low but P_j is too high and the overall effect on a major mode's cross elasticity depends on the strength of these two separate effects. Wardman (1991) shows that where the true share of the minor mode is low, such as 10-15%, which we might expect in many urban contexts, the proportionate impact of the scale factor effect is greater on the P_j than the α_j. This would therefore provide a tendency for the major mode cross elasticity to be too high.

5. ALTERNATIVE CROSS ELASTICITY ESTIMATION PROCEDURE

An attractive way forward, and one that we would in any event recommend to ensure consistency between recommended own and cross elasticities, is to deduce the cross elasticities from information on the own elasticities. Empirical work is being undertaken within this study to estimate own elasticities at a strategic level to supplement the evidence available from the review of the aggregate modelling literature. In any event, there is a much larger body of evidence on own elasticities than cross elasticities and indeed this was the approach adopted by Acutt and Dodgson (1995) in their work on cross elasticities. The relationship between cross and own elasticities was outlined by Dodgson (1986) as:

$$\eta^{i}_{xj} \leq |\eta^{j}_{xj}| \frac{S_j}{S_i} \tag{3}$$

where S_i denotes the market share of mode i and η_j is the elasticity of demand for mode i with respect to attribute x on mode j. If we have information on diversion factors, we can derive an exact relationship as:

$$\eta^{i}_{xj} = |\eta^{j}_{xj}| \frac{S_j}{S_i} \delta_{ji} \tag{4}$$

where δ_{ji} is the proportion of those diverting from mode j who switch to mode i.

In order to operationalise equation 3, we must adopt values for the own elasticities and here we shall restrict ourselves to price elasticities. On the basis of the review contained in Toner (1993), which amongst other things makes use of the review evidence contained in Fowkes et al. (1991) and Goodwin (1992), the own price elasticities for car, train and bus are taken to be -0.2, -0.8 and -0.4.

Although market shares will vary between the peak and off-peak, and also according to the network of public transport services, we here use a single set of figures relating to the journey to work for outer London, conurbations and other urban areas for 1992-94 (Department of Transport, 1995). The market shares of car, bus and train are 84%, 14% and 2%.

In order to operationalise equation 4, we additionally require estimates of the diversion factors. Acutt and Dodgson (1995) conducted a survey of transport operators and experts to obtain estimates of diversion factors and this is clearly an area for further empirical research. Our assumptions are set out in Table 14. The small proportions diverting to rail reflect the sparcity of the rail network whilst we take the not go category to include those who decide to walk or cycle.

Table 14: Assumed Diversion Factors				
	Car	Rail	Bus	Not Go
Car to:	-	10%	40%	50%
Rail to:	40%	-	40%	20%
Bus to:	20%	10%	-	70%

Table 15 provides the deduced cross-elasticities. The need to derive the exact relationships is quite clear in the case of the rail demand cross-elasticities since the upper bounds are so high as to be virtually meaningless.

Table 15: Deduced Cross Price Elasticities			
	Car Demand	Rail Demand	Bus Demand
Car Cost	-	≤8.40 =0.84	≤1.20 =0.48
Rail Cost	≤0.02 =0.008	-	≤0.11 =0.05
Bus Cost	≤0.07 =0.013	≤2.80 =0.28	-

Note: The ≤ figures are obtained from equation 3 and the = figures from equation 4.

It can be seen that the cross elasticities in Table 15 are generally much lower than those derived from the choice models. The low cross elasticities with respect to rail cost reflect the very low market share of rail which could not be replicated in the calculations undertaken in section 3 because the rail market share was not sufficiently low. Whilst the use of other elasticities, market shares and diversion factors will produce different results, the results are based on sensible assumptions and provide another indication that the cross elasticities derived from the disaggregate choice models are too high.

6. CONCLUSIONS

A large number of disaggregate mode choice models have been developed to explain urban travel behaviour in Great Britain. This paper has reported the key parameters of the models obtained from 34 studies. These models have been developed and applied in specific contexts where they can examine travel behaviour in some detail. However, the cross elasticities implied by such models will vary not only because the contexts are different but also because the market shares and the levels of the relevant travel variables will vary across different situations and these have a strong influence on the cross elasticities. We have observed appreciable amounts of variation in the cross elasticities across the situations to which we have applied the models. As Acutt and Dodgson (1995) state, " ..... any cross-elasticity estimates from one study will not be directly applicable to another because the cross elasticity values depend on the relative size of the two markets represented". We therefore avoid recommending a single set of cross elasticity values for urban travel.

Whilst we could use the disaggregate choice models to obtain cross elasticity estimates for the exact situation we would wish to forecast, this course of action is not recommended for the following reasons.

i) this study is concerned with regional and national forecasts and hence detailed disaggregate mode choice models are not needed. Indeed, there may well be difficulties in applying disaggregate models in a strategic manner given the amount of averaging that would be involved.

ii) as far as we are aware, models are not available which can specify the composition of the choice set and hence allow for those whose cross elasticities are zero. We have seen that this is a crucial requirement since the cross elasticities are otherwise too high.

iii) the models tend to exhibit very strong variation in the cross elasticity with respect to the level of the variables and, given that this has not been empirically justified, this is an undesirable feature.

Until these deficiencies are remedied, particularly the issue of choice set composition, we recommend that cross elasticities are deduced from own elasticities on the basis of relative market shares and diversion factors. Not only does this maintain consistency with theory and exploit the large amount of evidence on own elasticities, it does retain the dependence of the cross elasticities on market shares. However, it would still be worthwhile to compare the cross elasticities obtained by this means with a range of estimates obtained from the disaggregate choice models bearing in mind that the latter are expected to be too large.

Recommendations for further research are that there is a need to ensure that the market shares and particularly the diversion factors used to deduce the cross elasticities are as accurate as possible. Acutt and Dodgson (1995) conducted a survey of transport experts and operators to determine diversion factors and clearly there is a need for further empirical research here. In addition, models need to be developed so that appropriate allowances can be made in the application of disaggregate mode choice models to allow for what might well be significant proportions of travellers for whom a relevant cross elasticity is zero.

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