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DEMAND IMPACTS OF BUS QUALITY IMPROVEMENTS

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1. BACKGROUND

This papers stems from research commission by the Department for Transport (DfT) in 2007 entitled, *The Role of Soft Measures in Influencing Patronage Growth and Modal Split in the Bus Market in England* (AECOM, 2009). The key objective of the study was to investigate the role of 'soft' measures and how they influenced bus demand in England. A wide range of measures can come under the definition of 'soft' (Balcombe et al., 2004) and these can include driver training and attitudes; cleanliness; passenger information; security; accessibility; fares simplicity.

A number of studies in the past (SDG, 1996; Hensher & Priori, 2002; ACCENT, 2002) have used Stated Preference (SP) techniques to estimate valuations for these and other 'soft' measures. No attempt, as far as we are aware, has been made to estimate the direct demand impacts that result from the introduction of one, or more, soft measure onto a bus service. This therefore is the key difference between previous studies and the research reported in this paper.

With this in mind we report only the findings of the main SP modelling work that was carried out by ourselves within this project and specifically the elasticity demand models estimated from it. We note that this forms only a part of the overall research as carried out by ourselves and the lead consultant AECOM and which is reported in the final project report (AECOM, 2009). We also note at this point that the views outlined in this paper are entirely our own and do not necessarily reflect those of the DfT who commissioned this piece of research or of AECOM the lead consultant.

2. METHODOLOGY

The quantitative work associated with this study was based upon 10 case study areas chosen from across England. The 10 case study areas are listed below (Table 2.1), all of which had introduced a variety of soft measures in various combinations. In addition the mix of case studies offered a good spread of urban and rural areas with various levels of bus usage.

Table 2.1 Ten Case Study Areas and Soft Measures

Area	Soft Measures						
Poole	New LF Bus	On-Screen Displays	In-Vehicle Seating Plan	Trained Drivers	Climate Control	CCTV at Bus Stops	RTPI
Hull	New LF Bus	CCTV on Buses	Simplified Ticketing	New Interchange Facilities			
Tyne & Wear	New LF Bus	Trained Drivers	CCTV on Buses	Customer Charter	New Bus Shelters	Simplified Ticketing	RTPI
Kent	New LF Bus	Trained Drivers	Audio Announcements	Climate Control	CCTV at Bus Stops	New Bus Shelters	RTPI
Cambs.	New LF Bus	Trained Drivers	RTPI	New Bus Shelters			
Leeds	New LF Bus	On-Screen Displays	CCTV on Buses	Audio Announcements	Climate Control	New Bus Shelters	RTPI
Warrington	New LF Bus	Trained Drivers	RTPI	New Interchange Facilities			
Lancashire	New LF Bus	Trained Drivers	CCTV on Buses	Leather Seats	New Bus Shelters	RTPI	
Warwick	New LF Bus	Trained Drivers	Leather Seats	Customer Charter	New Bus Shelters		
Notts.	New LF Bus	Trained Drivers	CCTV on Buses	Simplified Ticketing	New Bus Shelters	RTPI	

LF – Low floor; RTPI – Real Time Passenger Information

A number of SP experiments were designed which addressed various aspects of the study (i.e. valuation of specific attributes) however only the main SP experiment, as reported in this paper, was administered to respondents in all 10 case study areas.

Whilst the SP exercises were conventional in the sense of offering choices between two modes, here car and bus, characterised by standard variables, such as time, cost, headway and bus type, the emphasis was upon directly estimated *demand elasticities* rather than valuations. This is because the purpose of the study was to estimate demand impacts rather than the more traditional approach of estimating values and then deducing the demand impacts by what these valuations would imply in conjunction with some reference fare or time elasticity.

Nonetheless it was possible to estimate conventional choice models to this data. This we have done and the results can be found in the main report (AECOM, 2009).

The design of the main SP was tailored towards two specific types of respondents:

1) Current Car Commuters – Here the design was based upon car commuters' choices between car and bus, where the emphasis was on making car less attractive and bus more attractive.

2) Current Bus Commuters – Here the design was based upon bus commuters' choices between bus, car and other possibilities, where the emphasis was on making bus less attractive and, for those with a car available, making car more attractive.

The attributes used to characterise bus were: fare; journey time; reliability, in terms of average lateness; frequency, in terms of minutes between buses; and bus type. The bus type could be the new bus relevant to the area and whether it was present or not. Two other levels were that the on-bus features only were present and the off-bus features only were present.

The attributes used to characterise car were cost, time and a combination of walk time from the car parking space and time spent searching for a parking space.

The attribute levels for time, cost and lateness were specified as proportionate changes on the respondent's current levels. If these were unknown, best estimates were used as defaults. The use of proportionate changes facilitates the modelling outlined below. Pre-specified levels were offered for frequency and bus type. Each respondent received 12 scenarios which were randomly drawn from a design of 80 possible scenarios.

As outlined earlier the bus users' SP exercise focuses on making bus less attractive. This is because they cannot make more bus commuting journeys as a result of bus becoming more attractive. Hence the demand function can only be specified for deteriorations on the current position. To do otherwise would lead to lower elasticities than the true market response. The same argument applies to the demand function specified for car commuters. However, we were concerned in the bus SP exercise to offer some scenarios where bus was improved, and this was the case in the second, fifth, eighth and tenth scenarios offered. These are not used in modelling.

The final SP designs for both car commuters and bus commuters were programmed into a CAPI based system with face to face interviews conducted in all 10 case study areas. The sample of bus users obtained was 1,146 all of which had a quality bus service in their area, with the focus on determining their reaction to the removal of the quality bus. For car users a total of 820 were surveyed. These did not have a quality bus service for their journey to work but there were such services in the area. In each case the respondent was shown a show card to illustrate what a quality bus looked like. It is worth noting at this stage that the overall study, and hence the main SP, was focused upon the commuting market and that all corresponding estimated demand elasticities refer to that specific market segment.

The CAPI questionnaire, in addition to the SP experiment, also contained a series of non SP questions (details of current commuting journey, how they rated services and socio-economic data) as well as questions about the SP experiment itself (i.e. how did they find it). We now outline our modelling approach and results.

3. MODELLING APPROACH & RESULTS

The modelling approach is based around analysis of changes in demand induced by the changes in bus and car characteristics. For each of the 80 scenarios offered, the number who remain with the mode in question is calculated and expressed as a ratio relative to the number in total who were offered that scenario and who currently use that mode. Thus the model takes the form:

$$\frac{V_N}{V_B} = \prod_{i=1}^{n} \left(\frac{X_{iN}}{X_{iB}} \right)^{\alpha_i} e^{\sum_{j=1}^{m} \beta_j (Z_{jN} - Z_{jB})}$$

If, say, current car users are analysed, then V_B is the base or total number who evaluated a particular scenario. V_N is the new volume of demand, that is all those who stated that they would remain with car.

X_i is any continuous variable, such as time or cost. Thus X_{iN} is the new level of the variable relative to the base level X_{iB} and thus the ratio is the proportionate change specified in the SP design. The α_i are therefore elasticities.

The Z_{jN} are dummy variables representing categorical variables in the new situation whereas the Z_{iB} relate to the base situation. Thus Z_{jN} might indicate the presence of a new bus, relative to a base Z_{IB} of an old bus. The β_j denote the proportionate change in demand from, in this example, the presence of a new bus. The model is estimated in the form:

$$\ln\left(\frac{V_N}{V_B}\right) = \sum_{i=1}^{n} \alpha_i \ln\left(\frac{X_{iN}}{X_{iB}}\right) + \sum_{j=1}^{m} \beta_j Z_{jN}$$

This modelling approach was used since it directly yields elasticity estimates which are easily interpreted and compared with other evidence. Rescaling relative to known elasticity evidence to allow for strategic bias is straightforward.

For both car and bus users, we report five demand models as follows, it should be noted that only models III, IV and V have time based changes. The model estimates can be found in Tables 3.1 and 3.2.

- I: Dummy variables specified for changes in on-bus, off-bus and both on and off-bus quality based on the data pooled across the original 80 SP scenarios offered.
- II: As I but the data is pooled only up to the area level, thereby allowing the ability to distinguish between the different bus types. Single parameters are estimated for changes in on-bus, off-bus and both on and off-bus quality.
- III: As II but for each area the bus quality changes are represented by the time valuations obtained from the unpacking SPs. The parameters vary by on-bus, off-bus and both on and off-bus change but are the same across areas for these three categories
- IV: As III but a single parameter is estimated to the time change that represents the bus quality change regardless of the type of change
- V: As IV but the effect of the bus quality change is allowed to vary with the level of frequency.

In Model I the weights in the weighted least squares estimation is estimated rather than imposed. In addition, and in the car users' models, 40 car users have been removed who in all 12 scenarios choose bus. The results tended to be highly plausible and consistent with other evidence on elasticities.

To allow for the different packages of bus quality changes across areas, disaggregation was undertaken by area type. Thus Model II only pools across the responses obtained in any area. The bus SP exercise was presented in all 10 areas. After removing those scenarios where there was no demand for bus in the new situation, 736 bus observations remained in the demand model.

The car SP exercises were administered in areas 1, 2, 3, 5, 7, 8 and 10, yielding 540 car observations.

It was observed that for both car users and bus users the larger data sets of Model II yield very similar parameter estimates to Model I. However, the goodness of fit is somewhat worse as a result of the fewer individuals making up any observation and hence the greater variability in the dependent variable, even after accounting for sample size through the use of weighted least squares.

Given the precision with which the bus quality demand impacts were estimated, and note that this was also an issue in the disaggregate modelling of the individual choice data, there was little point in specifying different dummy variables across areas.

Model III allows for the size of the change in quality by weighting the dummy variable on an area basis according to the time valuation of that change estimated in our unpacking SP. Thus if the unpacking SP estimated that the changes in Area Z have in total a 5 minute valuation whilst those in Area Y have a 10 minute valuation, the variable representing the change in quality would be 10 for Area Y and 5 for Area Z when these changes are observed in the data.

The coefficient estimates therefore indicate the effect on demand from a minute change in service quality regardless of what the actual service quality change is.

Note that this is not the same as using a generalised time approach. Whilst there are analogies in the use of composite terms, the demand impacts do not depend on the proportion that they form of generalised time.

For both the car users' and bus users' models, it is encouraging to find that a better fit is obtained by Model III compared to Model II the size of the quality change is considered.

What is found in Model III, where separate coefficients are estimated to the time change according to whether it is an on-bus, off-bus or both on and off-bus change (termed all-bus), is that for the car users' model there is no clear pattern. The imprecision of the off-bus coefficient estimate does not help matters when looking at the relativities between on-bus, off-bus and all-bus for all the models. For car users on-bus attributes seem to have more impact than all-bus attributes when both factors are significant (model III) which slightly muddies the water. It is not clear why this results has occurred although the relative imprecision of the coefficient estimates should be borne in mind.

Hence on grounds of sensible properties, Model IV where the coefficient is constrained to be the same regardless of the source of the quality improvement is preferred even though it is statistically inferior. The parameter estimate is closest to that for the new bus improvement, but it is this which occurs most often in the SP design.

In Model IV, a 13.75 minute improvement as in Area 1, which is the largest amongst the case studies (as estimated by separate valuation SPs), would be forecast to reduce car commuting by around 2%. The smallest improvement, of 7.02 minutes in Area 2, would be forecast to reduce car demand by around 1%.

For bus users, Model III indicates a larger affect per minute if both on-bus and off-bus (termed all bus) changes occur simultaneously. However, the precision of the parameter estimates is such that there is no confidence that there is a package effect at work here that implies a larger unit effect when more things are changed. Moreover, our unpacking models have found a striking similarity between the valuation of a package and the sum of the valuations of the package elements.

Even though Model IV is statistically inferior, we prefer this. It implies that the removal of Area 1's new buses would reduce bus demand by around 16.5%. Model V allows the bus quality effect to interact with service frequency. For car users, the effect is greater at lower headways, yet the hypothesis from the focus groups is that quality buses are more likely to succeed when a high level frequency is offered. The reverse is apparent here but a clear judgement cannot be made on this because for commuting journeys there is a tendency to find a concentration of high frequency bus services. For bus users, no clear pattern is apparent.

Table 3.1 Car Users' Models

<table>
<tr><th>Variables</th><th>Model I Estimates</th><th>Model II Estimates</th><th>Model III Estimates</th><th>Model IV Estimates</th><th>Model V Estimates</th></tr>
<tr><td>Constant</td><td>n.s.</td><td>n.s.</td><td>n.s.</td><td>n.s.</td><td>n.s.</td></tr>
<tr><td>Bus Fare</td><td>0.076 (7.1)</td><td>0.075 (7.4)</td><td>0.070 (7.1)</td><td>0.073 (7.5)</td><td>0.073 (7.3)</td></tr>
<tr><td>Bus Time</td><td>0.114 (6.3)</td><td>0.119 (6.8)</td><td>0.114 (6.6)</td><td>0.118 (6.9)</td><td>0.116 (6.5)</td></tr>
<tr><td>Bus Headway</td><td>n.s.</td><td>n.s.</td><td>n.s.</td><td>n.s.</td><td>n.s.</td></tr>
<tr><td>Late Time</td><td>n.s.</td><td>n.s.</td><td>n.s.</td><td>n.s.</td><td>n.s.</td></tr>
<tr><td>Introduce On Bus</td><td>-0.012 (1.5)</td><td>-0.013 (1.7)</td><td>0.0029 (2.6)</td><td rowspan="3">0.00149 (2.6)</td><td></td></tr>
<tr><td>Introduce Off Bus</td><td>-0.009 (0.8)</td><td>-0.006 (0.6)</td><td>0.0047 (1.6)</td><td></td></tr>
<tr><td>Introduce All Bus</td><td>-0.009 (1.4)</td><td>-0.008 (1.3)</td><td>0.0014 (2.3)</td><td></td></tr>
<tr><td>New Bus Head5</td><td></td><td></td><td></td><td></td><td>-0.0009 (0.9)</td></tr>
<tr><td>New Bus Head10</td><td></td><td></td><td></td><td></td><td>-0.0015 (1.9)</td></tr>
<tr><td>New Bus Head15</td><td></td><td></td><td></td><td></td><td>-0.0020 (2.3)</td></tr>
<tr><td>Car Time</td><td>-0.066 (3.2)</td><td>-0.075 (3.7)</td><td>-0.067 (3.4)</td><td>-0.070 (3.6)</td><td>-0.069 (3.5)</td></tr>
<tr><td>Car Cost</td><td>-0.062 (3.3)</td><td>-0.061 (3.4)</td><td>-0.056 (3.2)</td><td>-0.059 (3.5)</td><td>-0.061 (3.5)</td></tr>
<tr><td>SearchWalk</td><td>n.s.</td><td>n.s.</td><td>n.s.</td><td>n.s.</td><td>n.s.</td></tr>
<tr><td>Weight Power</td><td>-0.7</td><td>-1.4</td><td>-1.4</td><td>-1.4</td><td>-1.4</td></tr>
<tr><td>Adj R^2</td><td>0.620</td><td>0.201</td><td>0.215</td><td>0.210</td><td>0.209</td></tr>
<tr><td>Obs</td><td>80</td><td colspan="4">540</td></tr>
</table>

Note: Adj R^2 is for when an intercept is included; Note: Model IV is our preferred model; t-stats in ( ); n.s. not significant.
Note: In models I and II we specify dummy variables for the change in bus service quality hence the coefficients are negative. In models III and IV the bus service quality improvement is represented by a reduction in journey times (a negative term) hence the coefficient is positive.

Table 3.2 Bus Users' Models

Variables	Modal I Estimates	Model II Estimates	Model III Estimates	*Model IV Estimates*	Model V Estimates
Constant	-0.142 (6.4)	-0.147 (6.0)	-0.142 (5.8)	***-0.134 (5.7)***	-0.149 (5.4)
Bus Fare	-0.651 (11.2)	-0.703 (10.8)	-0.704 (10.9)	***-0.704 (10.9)***	-0.711 (10.9)
Bus Time	-0.224 (4.2)	-0.212 (3.5)	-0.213 (3.5)	***-0.217 (3.5)***	-0.164 (2.5)
Bus Headway	-0.109 (6.0)	-0.111 (5.3)	-0.111 (5.3)	***-0.111 (5.3)***	-0.097 (3.4)
Bus Av Late	-0.047 (3.4)	-0.051 (3.2)	-0.051 (3.2)	***-0.052 (3.3)***	-0.050 (3.1)
Remove All Bus	-0.117 (6.0)	-0.130 (5.8)	-0.013 (6.2)	***-0.013 (6.1)***	
Remove On Bus	-0.063 (2.2)	-0.047 (1.5)	-0.009 (1.8)		
Remove Off Bus	-0.003 (0.1)	-0.006 (0.3)	-0.007 (1.2)		
New Bus Head10					-0.014 (4.0)
New Bus Head15					-0.007 (2.0)
New Bus Head20					-0.009 (2.4)
New Bus Head30					-0.018 (4.5)
Car Time	n.s.	n.s.	n.s.	***n.s.***	n.s.
Car Cost	n.s.	n.s.	n.s.	***n.s.***	n.s.
Half Search & Walk	n.s.	n.s.	n.s.	***n.s.***	n.s.
No Search 1mWalk	n.s.	n.s.	n.s.	***n.s.***	n.s.
Weight Power	-1.5	-0.9	-0.9	***-0.9***	-0.9
Adj R^2	**0.734**	**0.210**	**0.211**	***0.212***	**0.215**
Obs	**72**	**729**	**729**	***731***	**728**

Note: Model IV is our preferred model; t-stats in ( ); n.s. not significant

The formulae for the calculations of changes in demand are set out below where T_2 is equal to generalised time after the introduction or removal of the quality bus and T_1 is equal to the generalised time before the introduction or removal of the quality bus.

Note that the valuations are taken from the unpacking exercise which are reported in the main report (AECOM, 2009). Using the package value (based on the sum of parts) for Area 1 (13.75 minutes) one can see that introducing the new package would reduce car commuting by around 2%, whilst taking the quality package away from an existing bus model would reduce bus demand by around 16.5%.

Car Users Model $e^{0.00149 * (T2 - T1)}$ *i.e. for area 1* $e^{0.00149 * (13.75)} = 0.9797$

Bus Users Model $e^{-0.013 * (T2 - T1))}$ *i.e. for area 1* $e^{-0.013 *(13.75)} = 0.8363$

Some care needs to be made when interpreting and comparing these numbers. The car users' model focuses upon the number of existing car users who will switch from car to bus. Quite how this translates through into additional bus users depends upon the relative sizes of the car and bus markets in the area for which forecasts are being prepared. In section 5 we address this issue in more detail and present forecasts.

5 Behavioural Response & Forecasts

In this section we look at who responded to the CAPI surveys carried out as part of the study and how that might influence the forecasts we can develop with regards the demand elasticity based models (bus users and car users) we reported in section 6.2. The bus users' model provides a useful contextual tool for seeing what the impact upon bus demand is if one removes existing soft bus attributes, however our principal forecasting tool is the car users' model. This forecasts the effects of improvements in bus quality as an elasticity based function, relating changes in car demand to changes in bus service quality.

The key factor to consider when making forecasts is that in all cases the respondents who were surveyed were making commuting journeys to the city/town centre from the suburbs/outer lying areas. This has important ramifications for forecasting the changes in bus demand as predicted by our demand elasticity models. The national mode share for commuting is 61% for car, 9% for car passengers and 7% for bus (Transport Statistics GB, 2008). If we based the bus demand forecasts upon these figures then a 2% modal shift away from car to bus commuting would lead to an increase in bus demand of just over 16% or a factor of 8 (this ignores car passengers), increasing to a factor of 10 if we treated car passengers as car drivers - both sizeable increases.

We know however that such forecasts would be misleading as the sample upon which our models are estimated from make commuting trips into the city/town centres from the suburbs/hinterlands of those same cities/towns, not commuting trips to other cities/towns. The ability to substitute bus travel for car travel is therefore considerable stronger for our sample and is not reflective of the national picture which also includes people who might, for example, be commuting between Leeds and Manchester, for which no viable bus service is available.

To illustrate this fact and its importance for the forecasts we have constructed **Table 5.1** which reflects the commuting modal split for a selection of major towns in West Yorkshire. We have used these figures to calculate an assumed mode split between car (65%) and bus (20%), with the figures for car including both car passengers and car drivers.

Table 5.1 West Yorkshire Cities Commuting Mode Split

Yr 2008	**% Modal Split**					
Cities/Towns	**Walk**	**Cycle**	**Motorcycle**	**Car**	**Bus**	**Train**
Bradford	4.6	0.2	0.3	71.3	17.1	6.4
Halifax	4.7	0.3	0.5	68.0	20.7	5.9
Huddersfield	6.3	0.4	0.4	59.1	25.7	8.1
Wakefield	3.7	0.4	0.5	69.6	12.6	13.2
Leeds	2.9	0.9	0.5	55.3	23.7	16.7
Proxy Average				**65.0**	**20.0**	
TSGB Figures				**70.0**	**7.0**	

Source: The West Yorkshire Local Transport Plan Partnership (2008)

Clearly there is considerable variability across the cities and towns outlined in **Table 5.1** and the mode splits for car are in most cases lower than for the national picture and the bus share considerably higher. This will have a dramatic effect on the bus forecasts and to illustrate this we have put together some demand forecasts using the car user demand elasticity model as outlined in section 4.

The forecasts (see **Table 5.2**) assume that a new package of soft bus measures worth 10.02 minutes (the average of our case study packages) is introduced to each of the towns and cities outlined in the table. This results in a set of forecasts that predict a modal shift away from car (1.48%) to bus. The impact this has upon bus demand depends upon the existing modal splits as outlined in **Table 5.1**.

The lowest changes in bus demand will be seen where the existing car share is relatively low compared to bus. This is the case in both Leeds and Huddersfield. Conversely the highest change in bus demand will come in cities were the car share is relatively high compared to the bus, for example Wakefield. Even then the Wakefield figures are around 55% of those forecast when the national Transport Statistics GB figures are used.

Table 5.2 Commuting Forecasts for West Yorkshire Cities

	Valuation of Soft Bus Measures (minutes)	**Modal Impact**	
Area		Change in Car Demand	Change in Bus Demand
Bradford	10.02	-1.48%	6.17%
Halifax	10.02	-1.48%	4.86%
Huddersfield	10.02	-1.48%	3.40%
Wakefield	10.02	-1.48%	8.18%
Leeds	10.02	-1.48%	3.45%
Assumed Average	10.02	-1.48%	4.81%
NTS Figures	10.02	-1.48%	14.80%

The forecasts presented in **Table 5.2** tell us that the ratio between existing mode splits will have an important role to play in the magnitude of the bus forecasts produced. They also highlight the danger of using the wrong type of modal splits. Mode splits are therefore a vital input into the forecasting procedure and will vary from city to city. For example, York reports commuting mode splits in it's Local Transport Plan of 47% for car and 7.4% for bus (here

20.6% walk), whilst Edinburgh reports (Edinburgh Local Travel Survey 2007-2011) splits of 35% for car and 30% bus (again walk is strong at around 20%).

This discussion leads us onto a more detailed consideration of the forecasts for the ten case studies considered in this project. These are illustrated in **Table 5.3** and are based upon the same procedures as were used to produce the forecasts outlined in **Table 5.2.**

The new forecasts (**Table 5.3)** range from a 3.38% increase in bus patronage up to 6.57%, with an average increase of around 4.81%. Clearly the forecasts are somewhat artificial in that we have assumed a generic commuting mode choice split of car (65%) and bus (20%) when we should be applying area specific mode splits. At first glance the forecasts seem very plausible but how do they stack up against existing evidence?

Table 5.3 New Area Forecasts

		Attribute Valuation (minutes) [1]	**Modal Impact Driven by Car Model**	
Area	**Number of Bus Soft Attributes**	**From parts**	**Change in Car Demand**	**Change In Bus Demand**[2]
Poole	7	13.75	-2.02%	6.57%
Hull	4	7.02	-1.04%	3.38%
Tyne & Wear	7	12.03	-1.78%	5.79%
Dartford	7	12.56	-1.85%	6.01%
Cambridge.	4	7.18	-1.06%	3.45%
Leeds	7	10.85	-1.60%	5.20%
Warrington	4	7.37	-1.09%	3.54%
Burnley	6	10.81	-1.60%	5.20%
Warwick	5	7.45	-1.10%	3.58%
Nottingham .	6	11.16	-1.65%	5.36%
Average	***5.7***	***10.02***	***-1.48%***	***4.81%***

[1] This is based upon SP experiments conducted as part of the study but not reported in this paper see AECOM (2009) for further details.

[2] This is based upon an assumed commuting modal split of car driver + car passenger (65%) and bus (20%).

The use of actual patronage evidence from the 10 case studies and other external evidence might provides us with a sense check but there is a problem in that it is difficult to disentangle the impacts of different attributes since few are introduced independently of other, 'soft' or 'hard' interventions, so determining the actual effect of each factor can prove difficult.

In addition the changes to concessionary fares legislation in recent years has compounded the problems in estimating patronage impacts and these need to be netted out to see the true impact.

A further problem encountered when comparing patronage growth across routes is if one does not take into account the base from which patronage growth is based. Large increases can often be the result of a low starting point.

A study carried out by Cairns et al (2004) reminds us that whilst soft bus interventions changes can result in an initial increase in patronage, it is estimated to take two years for the full affects to be appreciated. Again this can create problems for estimating and comparing patronage impacts.

The largest problem however preventing a like for like comparison is related to the fact that our forecasts are based upon the commuting market and so any like for like comparison would have to take this into account.

We would suggest that the forecasts provided by our models are more relevant to established bus services were the main focus of change is the introduction of bus soft measures rather than bus services which are being transformed by a mixture of both hard and soft measures or which are building from a relatively small base to being with.

With this in mind the “Routes to Revenue Growth” report probably provides the best contextual evidence. The report examined nine case studies involving either, route specific or network changes (The Ten Percent Club, 2006). Some related to Quality Partnership, others were independent of them. Each was based upon existing routes or networks and each reported patronage growth against a background decline. The key changes are outlined below in **Table 5.4.**

Changes do include ‘hard measures’ such as improved frequency but combinations of soft measures have also been introduced. These include vehicle specifications, information provision, security improvements and marketing measures. However, they offer a picture which is more in line with our results, although in all cases the patronage forecasts are not specifically for the commuting market.

Table 5.4 Routes to Revenue Impacts

Routes	**Change in Patronage**
Route 36 – Ripon, Harrogate & Leeds	+18% per annum
Witch Way – Nelson, Burnley, Rawtenstall & Manchester	+16% per annum
‘More Routes’ – Poole & Bournemouth	+10% per annum
Rainbow 5 – Long Eaton & Nottingham	+8% per annum
‘Showcase Routes’ - Bristol	+3% per annum
Networks	
Corby Star Network	+30% per annum
Go2 Network	+18% per annum
Brighton & Hove Network	+5% per annum
Medway Towns Network	+4% per annum

Source: The Ten Percent Club (2006)

Clearly there is a difficulty in making like for like comparisons with other schemes in terms of the mix of ‘soft’ and ‘hard’ attributes used; the problem of separating out ‘extraction effects’ from parallel routes; netting out concessionary fares effects; determining the counter factual decline in bus markets over time; and focusing purely on the commuting market. What we are able to say with some confidence is that our forecasts do not tend to exceed the impacts described in other studies and when one takes into account the factors just mentioned they appear very plausible.

6 CONCLUSIONS

In contrast with previous work in this area, our efforts, as reported in this paper, have focussed upon the demand impacts of bus service quality improvements rather than valuations of them per se.

From amongst a range of models, developed for a variety of purposes, the principal model for forecasting the effects of improvements in bus quality is an elasticity based function, relating changes in car demand to changes in bus service quality. The changes in bus service quality are specified in time units and were obtained from a separate SP exercise dealing specifically with the valuation of various aspects of on and off bus quality improvement. For example, in Poole the value of the on and off bus quality package is worth 13.75 minutes whereas in Cambridge the value of the quality package is worth 7.18 minutes.

In terms of forecasting the change in bus patronage we can use these bus quality values in conjunction with our demand elasticity model. This results in the model predicts a 2.02% reduction in car demand in the case of Poole and a 1.06% reduction in the case of Cambridge.

The proportionate increase in bus demand depends upon the relative shares of the two modes. Taking car to have a 65% share of entries to the central area for commuting purposes, as opposed to 20% for bus, would imply a 6.57% increase in demand for bus in Poole and a 3.45% increase in demand for bus in Cambridge.

The model can handle other types of improvement, beyond those contained in the main study (AECOM, 2009), so long as the improvement can be specified in time units. As such this makes it a very powerful and versatile forecasting tool.

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