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ESTIMATING THE DEMAND FOR URBAN BUS TRAVEL

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ABSTRACT

The disadvantages of conventional transportation study models, in particular their large data requirements and their weaknesses in dealing with changes in trip generation rates have led to a need for a simple model that can quickly and at low cost examine alternative public transport strategies.

This paper investigates simple economic models of bus demand, examines alternative variables that can be used and discusses some alternative model forms. It demonstrates the results of a model using data from twelve urban bus operators in Britain and compares the results with those from other types of study. The model utilises fare and service quality elasticities to explain the decline in passengers on urban bus services, and derives an average elasticity with respect to fare changes of –0.31 and with respect to service quality changes of +0.62. It is estimated that fare rises accounted for 13% of the 43% decline in passengers over the last fifteen years, vehicle mileage reductions for 14.3% and that only 15.7% was due to such factors as rising car ownership which are often given as the cause of declining bus patronage.

The results, by showing that passengers are far more sensitive to changes in service than they are to fare rises, are a useful guide to the broader public transport policy issues, and the paper concludes that the model does provide a useful method of forecasting public transport demand at a strategic level. Further work is needed, however, to establish more accurate forecasts for different types of passenger and studies are now being undertaken to establish these and to construct an operational forecasting model that can be applied with only limited data requirements

Introduction

Estimates of bus passenger demand have always been important to bus operators and to transport planners. Recently they have taken on a new importance with the discussion of subsidies, interest in improving public transport and, for British local authorities, the need to formulate transport policies and programmes. The need for a clear understanding of the impact of the determinants of demand, the manner in which patronage reacts to changing fares and services, the manner in which social groups are affected and so on are issues fundamental to the definition of policies for public transport development. In this context it is surprising that although some evidence is available on fare elasticities (Kemp, 1973; Daly and Gale 1974) and some operators have made their own internal studies (Fairhurst, 1973), little evidence has been published on the critical issue of the interaction between patronage and service quality (see also Moran and Jones in this issue).

Forecasting public transport demand by the use of conventional transportation study models requires massive data collection exercises. These include not only expensive home interview surveys but also the collection of detailed information on road- and public transport networks and the building of elaborate computer-based representations of these networks. Even then the resulting models have often proved inadequate to satisfactorily predict public transport patronage.

The conventional transportation study model was intended to evaluate highway improvement schemes under conditions where the level of service would not change greatly. Therefore, despite the complexity resulting from the level of geographical detail, the underlying behavioural mechanisms modelled are over-simplified whilst person types are not sufficiently disaggregated. One particular problem is the inability of trip generation models to respond to changes in the overall quality of transport service. Since changes in the level of bus use in European countries generally result not from the diversion of private car trips but from increases in trip making by persons without access to a car or persons diverted from walk trips, the errors in estimates of trip levels can be serious. Shortfalls in the predicted level of bus use have lead to financial problems for operators and have meant higher fares and reduced services, which in turn have caused further declines in use. These effects have led to the situation in one British new town where the current level of bus use is less than a third of that predicted by conventional transportation study models when the bus system was designed.

Recent developments of the conventional model such as the models of individual demand (Richards and Ben Akiva, 1974) or "strategic" models of the "CRISTAL" type (Tanner et al, 1973) have taken into account many of these problems, particularly by extending trip generation to include walk and cycle trips. Nevertheless they are still relatively expensive exercises involving much data collection and complex models, the parts of which interact in a way that even experienced transportation planners may find difficult to understand completely.

Unlike highway proposals which because of their long implementation periods and heavy capital investment require long term traffic forecasts, public transport policy issues are more often concerned with proposals for immediate action and require short term forecasts – the elaborate synthesis of future travel requirements is usually not necessary since the existing pattern of demand can be taken as a base for the changes. In the light of this, Colin Buchanan and Partners have undertaken a programme of research to construct a simple model capable of predicting the effects of different public transport policy measures. This paper reports the results of the first stage of that work. It discusses various aggregate economic models of the demand for bus travel and presents the results of a study of twelve urban bus undertakings in Britain.

Alternative Approaches to Estimating Public Transport Demand

There are four main approaches to estimating the factors affecting public transport demand; these are discussed at length by Smith and McIntosh (1974).

i. SPECIAL EXPERIMENTS

These involve monitoring the changes resulting from some specific policy or operational measure. Examples are the Stevenage Superbus experiments (Buckles, 1974) and various bus demonstration projects such as the provision of a bus feeder service to a local station (Department of the Environment, 1974).

ii. ANALYSIS OF TRAVELLERS' CHOICE OF MODE

The data are gathered either from transportation study home-interview surveys or from special studies. This method provides a good source of individual data but involves high collection costs.

iii. CROSS-SECTIONAL COMPARISONS BETWEEN TOWNS

This involves comparison of the numbers of public transport trips undertaken in different towns. Basic data on trip rates, population, car-ownership etc. are easily obtainable, but it is also necessary to take into account all other differences between the towns studied. These include such intangible factors as the "level of congestion" and factors difficult to quantify in a single variable such as the "degree of centralisation" of travel movements. Nevertheless, useful results can be obtained (Wabe and Coles, 1975).

iv. TIME–SERIES ANALYSIS OF BUS–OPERATOR's DATA

This approach may be at an aggregate level using the total number of passengers or passenger-miles for the whole undertaking or, if more detailed information is available, for individual routes, journeys of specified length, or journeys at a particular time of day. It depends on the availability of data in a consistent form over a sufficiently long period. For this approach data is probably most readily obtainable and it provides a useful background to the consideration of more detailed studies. The principal disadvantage is the over-simplification involved in the averaging of responses over different types and lengths of journey.

We have chosen to adopt the time-series approach and subsequently discuss the difficulties of the method and its limitations. Surprisingly we have only one other study of this type seeking to compare different operators, the work undertaken by Ian Black in the Department of the Environment some years ago, (Department of the Environment, 1971), details of which were only published after completion of our study (Smith and McIntosh, 1974). The methods used here are similar to those adopted by Black, although the form of model used is different. Black used data from the quarterly returns provided by bus operators to the DoE over a period of six years. His results gave a mean fare elasticity of – 0.31 and a mean service elasticity of +0.71. However, his results show considerable unexplained differences between different towns with a range of service elasticities from +0.17 to +1.12; yet on this basis average values have been used for several different purposes (DoE, 1971; Hill, 1973). Clearly examination of a larger sample of operators and more detailed discussion, particularly of service elasticities, is needed if the results are to be used for demand projections and in the definition of public transport strategies.

The demand for bus travel is extremely complex. In the first place, it is not just affected by fares but also by times spent in vehicle, waiting and walking, discomfort and irregularity. These can often be simplified into the concept of the "generalised cost" of a journey, but only if we can attach weights to each of its components. Secondly, urban bus travel is a commodity differentiated both in time and space and consumed by a heterogeneous population. As a result costs to passengers and behavioural responses to changes in costs will not be the same for all types of person, all trip purposes, all times of day, all routes, and so on.

It is convenient to consider demand in terms of elasticities, the elasticity of demand being the proportionate change in demand resulting from a change in a variable while keeping other factors constant, divided by the proportionate change in that variable. For example, the fare elasticity is defined as:

$$\alpha = \frac{(P_2 - P_1)/P_1}{(F_2 - F_1)/F_1} \text{ or } \frac{\%\text{ change in demand}}{\%\text{ change in fare}} \tag{1}$$

This definition is called the "arc elasticity" or "shrinkage ratio" (Kemp, 1973), and refers to a finite change in the variables. An alternative definition is the "point elasticity" defined as:

$$\alpha = \frac{dP \cdot F}{dF \cdot P} \tag{2}$$

Which can be estimated from a finite change by the definition:

$$\alpha = \frac{\log P_1 - \log P_2}{\log F_1 - \log F_2} \tag{3}$$

The difference in the definitions is the difference between the slope of line X_1, X_2 and the slope of the tangent to the demand curve at X_1. However, in practice the difference between the two definitions is insignificant; for example with a 10% fare change the difference in α is less than 0.01.

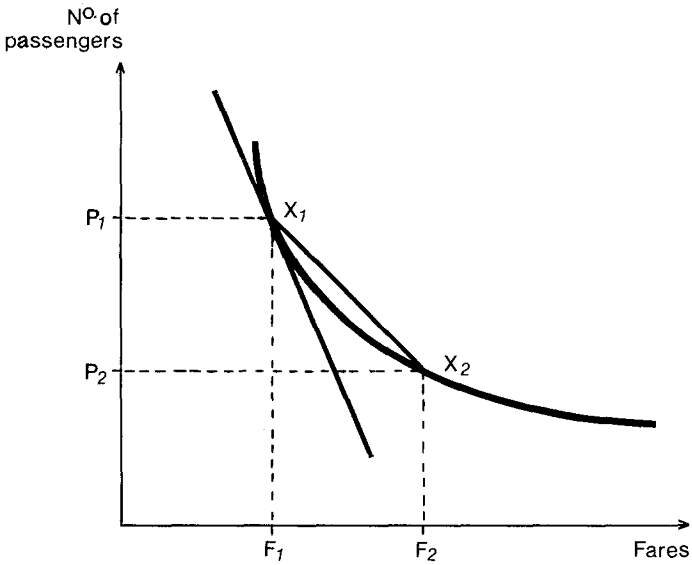

Fig. 1. Illustration of a constant elasticity demand curve.

The Variables Used in our Model

To develop a simple model we require variables to measure the demand for bus travel itself and the underlying factors affecting demand such as the cost, time, comfort and convenience elements of generalised cost, the availability of alternative modes and the total demand for travel of any kind in the area.

THE DEMAND FOR BUS TRAVEL

Since reactions to both fares and service intervals will differ according to the length of journey, ideally demand should be measured in terms of the number of trips of each journey length. Unfortunately, data constraints mean that we must normally use an aggregated measure of demand such as receipts, passengers or passenger-miles.

Considering numbers of passengers alone is liable to overstate the real decline in bus ridership, since it will be partially offset by increases in journey length. So in some respects passenger-miles makes a better demand variable. Unfortunately few undertakings have prepared estimates of passenger mileage, and even in these cases it is normally an estimate from the numbers of tickets of each value sold. Its accuracy – particularly when fare steps are changed in a fare increase – is uncertain and consistency in methods between undertakings is impossible to ensure. Operators would normally prefer receipts as a measure of demand but in order to make direct comparisons with the results of transportation studies we have chosen to use the numbers of passengers.

THE MONEY COST OF BUS TRAVEL

The level of fare can be proxied by the average revenue per passenger carried, adjusted for changes in the value of money using the Retail Prices Index for each time period. This adjustment will of course be subject to all the usual difficulties of price indices and it could be argued that an index of fares relative to wage levels would be more appropriate. Alternatively we could use a price index for substitute goods, but these would be hard to identify.

The measure of fares used (average revenues per head) is not perfect since it will be affected by any changes in average trip lengths. Changes in trip lengths have been estimated by Tyson (1974) for one municipal operator, where he found that the average trip length increased by 3.6% per annum between 1960 and 1969. According to the relationship he derived between fare paid and length of journey, this would imply that an average increase of 1.8% per annum in fare levels was due solely to longer trips. However, this town was probably an extreme example, with a considerable amount of redevelopment in its inner areas; on average increases would not be as great.

THE LEVEL OF SERVICE PROVIDED

The only readily available measure for the level of service is the number of vehicle miles run. In so far as changes in vehicle miles represent changes in service frequencies this will be inversely proportional to average waiting times. However, changes in vehicle miles could also be due to changes in route lengths, or to the cutting of routes, and obviously the effect in terms of access to the bus stop, walking times, and waiting times will not have any consistent relationship to the vehicle mileage run. Cuts in vehicle mileage are also frequently due to staff shortage which will have a different effect from "planned" cuts in service: the increase in passenger waiting times will be much greater, but since these cuts are either not foreseen or expected to be only temporary, passenger numbers may not be immediately affected.

Whereas fare changes are usually applied fairly uniformly across all routes and groups of travellers (although they may differ between different journey lengths) changes in vehicle mileage frequently have a more local incidence. They will differ between routes or between peak- and off-peak services and it is not justifiable merely to average demand responses. Cuts on a fairly frequent service will not increase average waiting times by as much as a reduction of the same proportion of a less frequent service – reduction from five minutes to ten minutes headways is likely to have less effect than a reduction from ten minutes to twenty minutes headways. Over several years if service frequencies continue to decline further cuts can be expected to have an increasing effect on patronage.

Apart from their effect on waiting times, service cuts may also reduce passenger comfort through overcrowding or lead to a large increase in the number of passengers left behind because the bus was full by the time it reached their stop. Moreover, higher loads may lead to delays to buses and hence a tendency to increased "bunching" and longer waiting times. These factors are only likely to be important at peak periods, but subjectively we feel that comfort may be valued highly by bus users and these factors could cause a switch to other modes. In particular, buses full on arrival may cause many potential users to walk rather than wait for the next bus. Unfortunately we do not have data separately for peak periods and so cannot test our hypothesis. However, we suggest that service elasticities may be high at peak periods and differences in the extent of cuts in peak- rather than off-peak services may lead to differences in the values of service elasticities discerned in different towns.

OTHER FACTORS AFFECTING DEMAND

Other factors affecting demand are not explicitly modelled, but are presumed to be represented by the time trend. These include changes in the speed and reliability of buses, costs of alternative modes, the effects of rising car ownership, population growth, falling population density (which with a constant vehicle mileage implies a fall in the standard of service), increased traffic congestion, changes in the distribution of work places and other travel destinations.

In general most changes will take place fairly evenly over time and hence will be modelled in the time trend. However, there may have been significant unmeasured changes in the case of individual bus operators:

marketing strategies may alter, services be completely reorganised, or journey times may change as a result of the introduction of one man operation, new traffic management schemes, etc. If these shifts in demand are postively correlated with a variable, the elasticity with respect to that variable will be overestimated, if negatively correlated, the elasticity will be underestimated.

One major effect which is not adequately modelled by our analysis is the introduction of one man operation. This causes delays in boarding and so longer journey times, irregularity of service resulting from bunching, and longer waiting times. An attempt was made to model this effect for the two towns for which data was available, but, due possibly to deficiencies in the data, no significant relationship was observed.

Choice of Model Form

We considered a number of alternative models of demand – these express P, the number of passengers, in terms of F, the average fare revenue per head, V the number of vehicle miles and t a measure of time (in years). The aggregate nature of the data with a comparatively small number of observations for each run made it essential to use a comparatively simple model. The simplest forms are:

a. linear $P = a + bF + cV + dt$ (4)

b. constant elasticity $P = BF^{\alpha} \; V^{\beta} \; e^{-\gamma t}$ (5)

Use of a simple linear model would be unrealistic with the large decline in bus patronage observed, as it would, if projected, soon predict negative numbers of passengers; we therefore chose to use a model with constant elasticity with respect to both fares and vehicle mileage. The other factors affecting demand are assumed to be represented by a time term or are left as an unexplained residual.

There are two ways in which we can make this constant elasticity model linear in order to estimate the elasticities:

i. taking logarithms: $\log P = \alpha \log F + \beta \log V + \gamma t$ (6)

ii. modelling the annual percentage changes in each variable:

$$\Delta P = \frac{dP}{dF} \Delta F + \frac{dP}{dV} \Delta V + \frac{dP}{dt} \tag{7}$$

(where ΔP, ΔF, ΔV are the annual changes in each variable.

From equation (5) $= \dfrac{\partial P}{\partial F} = \alpha BF^{\alpha - 1} V\beta \, e^{-\gamma t}$ (8)

$$= \alpha \frac{P}{F} \text{ etc} \tag{9}$$

$$\text{So } P = \alpha \frac{P}{F} \Delta F + \beta \frac{P}{V} \Delta V - \gamma P \tag{10}$$

putting $\hat{P} = \Delta \frac{P}{P}$ etc we get the equation

$$\hat{P} = \alpha \hat{F} + \beta \hat{V} - \gamma \tag{11}$$

i.e. that the percentage change in passengers is a linear function of the percentage changes in F and V.

This second method does in fact involve a slight approximation in that it assumes the changes in P, F and V to be small between observations – we are measuring arc elasticities rather than point elasticities – but the likely errors from this will be extremely small.

We have chosen to use the second form of the equation – involving the annual percentage changes in passengers, fares per head and vehicle miles. The differences between the forms is discussed in Appendix A.

As with any simplified approach, this model has a number of weaknesses. First it assumes that elasticities are constant. Our observed elasticities are aggregations over different person types, different trip purposes, short and long trips, each of which will have different responses and may be faced with different cost changes. Changes in the composition of bus passengers will change the average elasticity value. Elasticities may also change as we move along the demand curve or through time. The value of the elasticities may well have changed during the period of observation and so we must regard the "constant" elasticity measured as only an approximation to the actual value and must be careful in extrapolating outside the range of observations. This model is unsuitable for example, for examining a free fares policy, since with zero fares it would predict that the number of passengers would be infinite; In order to examine policies such as free fares, it would be better to use a constant elasticity function with respect to generalised cost.

$$\text{i.e. } P = k\,(aF + bT_1 + cT_2)^{\alpha} \tag{12}$$

where T_1 is journey time and T_2 waiting time. This would require more data than were available to us, as would the other alternative – a logistic model which involves fitting an S–shape curve, to assumed maximum and minimum levels of bus ridership.

Changes in the level of demand may also take place because of changes in the price of substitute forms of transport or through population and economic changes through time; changes in income and the level of economic activity will alter the level of demand for travel in general, as well as affecting the rate of growth of car ownership. Other changes may include the result of changes in the amount of leisure and the way it is spent.

These shifts are allowed for in our model by the time trend: we assume that the demand changes by a constant annual amount each year. If changes are taking place smoothly over time they will be adequately modelled by our equation. Problems occur when sudden changes take place, such as a rapid rise in fuel prices or where fluctuations occur in the level of economic activity, in incomes and car ownership. Whilst the price of the principal alternative mode, cars, has fallen over the period, this has been at a fairly steady rate. The 1956 Suez Crisis and the 1973–4 fuel crisis both lie outside the period studied and the only sudden changes in the costs of car use were changes in car purchase tax in 1963, which would only have an extremely small effect, and increases in fuel tax in 1964 and 1968. The model could, however, have been considerably improved by the inclusion of an index of car ownership or of the level of economic activity. However, whilst details of the number of cars registered in each town could have been obtained these do not give an accurate idea of the actual number of cars being used in that town.

Another problem is the nature of responses – passengers may either be slow to respond to the change or else people may initially overreact to fare increases and then return to their former habits. We examined the possibility of lagged responses, but felt that any lag would be considerably shorter than a year and would make no significant difference in our results.

We must also consider the direction of causation – declines in passenger numbers could lead to fare increases or service reductions so there are two simultaneous relationships between passengers, fares and vehicle mileage; we must be careful that we have correctly indentified the curve we are estimating. In fact, a study of a typical operator's profit and loss account reveals that fare increases usually occur after a loss has already been incurred. Considerable lags exist between a decline in passengers and resulting fare increases and it is unlikely that the relationship is wrongly identified.

The Empirical Analysis

Data for this study were obtained from 16 urban bus operators in towns of over 100,000 population. These operations were all run by the local authority, and towns were selected where the figures were not distorted by the formation of a metropolitan Passenger Transport Authority (PTA) or by a large amount of joint-running with interurban and rural services provided by the National Bus Company (NBC). Towns where the entire service was provided by a National Bus Company subsidiary were not used because of the difficulty of separating figures for urban and rural operations. Allowances were made for changes in the areas covered and operators were specifically asked whether there were any unusual factors, such as the taking over of National Bus Company routes during the period.

Data for four towns had to be rejected because of changes in the area covered or amount of joint-running for which it was impossible to adjust. In most cases, data for the financial years ending March 1960 to March 1973 were used and the analysis was based on passengers carried, vehicle miles in

TABLE 1

Estimated Fare and Service Elasticities (standard errors are shown in brackets)

Town	Constant	Vehicle miles elasticity	Fare elasticity	R^2
Coventry	– 0.54931	+0.81848	– 0.33215	0.90
		(0.11370)	(0.05595)	
Leeds*	– 1.62528	+1.01483	– 0.32410	0.87
		(0.29858)	(0.07304)	
Derby	– 1.22403	+0.52098	– 0.40791	0.81
		(0.11506)	(0.11847)	
Portsmouth	– 1.66039	+0.63245	– 0.17917	0.77
		(0.16154)	(0.08009)	
Cardiff	– 0.07561	+0.97582	– 0.44975	0.76
		(0.34806)	(0.20842)	
Northampton	– 2.12092	+0.70159	– 0.37473	0.75
		(0.13086)	(0.17589)	
Plymouth	– 0.41174	+1.19426	– 0.34802	0.71
		(0.24761)	(0.12703)	
Glasgow	– 3.15069	+0.21878	– 0.25445	0.71
		(0.17363)	(0.05818)	
Bradford	– 1.21073	+0.42438	– 0.39945	0.68
		(0.18891)	(0.09884)	
Sheffield	– 2.22627	+0.34659	– 0.16574	0.58
		(0.19317)	(0.07202)	
Southampton	– 1.79128	+0.26826	– 0.25239	0.53
		(0.25602)	(0.11282)	
Leicester	– 1.17474	+0.30023	– 0.23590	0.52
		(0.20539)	(0.06889)	
Mean Values	– 1.42	+0.62	– 0.31	
Regression on data for all towns together	– 1.3534	+0.63036	– 0.30542	0.70
		(0.05143)	(0.03169)	

* The Leeds equation also incorporated a dummy variable to explain a sharp change in the observed pattern in the last two years, see Appendix B.

service and average revenue per head. In addition to the regression equations for the individual towns, an overall equation was produced using data for all towns and incorporating a dummy variable for each town – in effect this equation produces fare and vehicle mileage elasticities that give the best fit to all the towns and allows the constant to take a different value for each town.

Despite all the potential weaknesses, the results of the analysis are extremely satisfactory, considering that we were attempting to explain variations from the time trend and not the actual number of passengers. In making comparisons with the double logarithmic form of equation, used by Black (Smith and McIntosh, 1974) it should be remembered that that form will give extremely high values of R^2 simply because the time trend will itself explain a considerable part of the variance. Our variable form eliminates this. For example, using the logarithmic form of equation for Glasgow, we obtained a value of R^2 of 0.999, yet our equation to explain percentage changes only gave a value of R^2 of 0.71. The values of R^2 obtained are generally about 0.7 although they cover a range from 0.90 down to 0.52. The coefficients for fares and service quality elasticities agree well with a priori expectations. All have the right signs and are of the size we would expect. Both the range of values and the standard errors are smaller for fare than for vehicle mileage elasticity. This is as we would expect for the effects of different kinds of vehicle mileage changes will not be uniform.

Each estimate also shows its standard error in brackets and estimates are normally taken to have a confidence range plus or minus 2 standard errors. These standard errors are quite large, which is only to be expected from the very small number of observations (usually about 12) available for each town. The differences between the estimates for individual towns therefore largely fall within the range of error that can be expected, although Coventry and Plymouth do have a significantly higher and Glasgow a significantly lower vehicle mileage elasticity. The range of fare elasticities about their mean of -0.31 is no more than the normal range of error of the estimates.

Of greater interest is the equation for all towns combined. This showed that the changes in patronage could adequately be explained by a model which assumed vehicle miles and fare elasticities were the same for each town, but which did allow the constant term to differ between towns so as to account for differences in population growth and similar factors. This combined model overcomes the problem of having only a few observations for each town. The resulting standard errors are very much smaller suggesting that the differences in estimates between different towns are not generally real ones but stem from the range of error in the estimates.

Thus, we confirm previous evidence that bus ridership is much more sensitive to service quality than it is to fare levels. The small standard errors of the fare and service elasticity estimates in the combined equation indicate that the results of the equation can be used to adequately predict the likely effects of fare and service changes in overall policy issues. However, the standard errors of service elasticities for individual towns were large and further investigation is necessary before we could establish a likely value for service quality in individual examples. This is not surprising in view of the disadvantages of vehicle mileage as a proxy measure for service quality.

A Comparison with the Results of Other Types of Study

RESEARCH BY LONDON TRANSPORT

London Transport have studied detailed information for the years 1970–72 (Fairhurst, 1973) separately analysing weekday and week-end travel using data for four-week periods.

In addition to the level of fares and vehicle mileage run the model used the weather as a variable and adjusted for lags in response. Results were produced separately for each of the two years studied. This study showed a fares elasticity of – 0.25, although this was the result of changes in certain fares only, and an overall fare elasticity was estimated to be – 0.3. The vehicle miles elasticities produced were rather inconsistent, being +0.67 in the first year and +0.15 in the second. This was explained by the type of services affected – cuts in the first year were on suburban routes where conditions can be expected to be similar to those in provincial towns whilst cuts in the second year were concentrated on the most frequent services. It was shown that the difference in elasticities could be explained by a generalised cost model similar to that presented below.

Another study (Fairhurst, 1972) of the effects of one-man operation gave a vehicle mileage elasticity of +0.65 for 30 suburban services with an average headway of 12 minutes. This was produced by a different type of regression model using data for specific routes and which sought to break down the change in passengers associated with conversion to one-man operation.

A CROSS SECTIONAL MODEL OF DEMAND FOR BUS TRAVEL

Few studies have succeeded in plausibly explaining the differences in bus use between towns. However, Wabe and Coles (1975) have recently adopted this approach to study the demand for bus travel in 30 British towns. Although the cross-sectional approach makes it difficult to include all relevant differences between towns it does have the advantage of enabling separate estimates of fare and service elasticities to be made for peak and off-peak periods. Wabe and Coles have used census journey-to-work data to separate the numbers of work and non-work journeys. The variables used were the estimated fare per passenger-mile, the annual number of bus miles run per head of population, the population of the town and the number of cars registered per employee. The models explained the proportion of work trips by bus and the annual number of non-work trips by bus per head. Their results gave fare elasticities of – 0.19 for work journeys and – 0.49 for non-work journeys; the elasticities with respect to vehicle miles were 0.58 for work journeys and 0.76 for non-work journeys. Thus, the coefficients obtained agree well with our own work and support the conclusions of the London Transport and the Stevenage study that off-peak elasticities are much higher. However, the model suffers from fairly high standard errors and as in all cross-sectional models using aggregated data it is difficult to ensure that unmodelled differences between towns are not correlated with those modelled and hence affect the estimates of coefficients obtained. In particular, it is impossible to determine the direction of causation – is it higher fares that lead to lower patronage or lower patronage that lead to higher fares?

SPECIFIC CASE STUDIES – STEVENAGE "SUPER BUS" EXPERIMENT

The figures used here are drawn from the technical report on the experiment (Buckles, 1974). Fares and frequencies were changed in a number of phases. This causes problems in identifying their impact for it took four or five months for each change to take full effect on the numbers of passengers. Moreover, the continuing advertising and marketing campaign may have had a considerable effect on passengers. For the last fare reduction Smith and McIntosh (1973) calculated fare elasticities of – 0.27 for peak trips and – 0.87 for off-peak trips.

Service frequencies were increased twice. At the start of phase 2 peak frequency improved slightly from 8 mins. to 7½ mins. and off-peak frequency improved from 12 to 7½ mins. At the same time the introduction of a new fare collection system greatly improved journey times and the regularity of services, and the route length was cut. These changes make it difficult to separately identify the effect of the frequency change. The second change was a further increase in frequency from 7½ mins. to 5 mins. during the day and from 15 to 10 mins. in the evenings and on Sundays. Rather surprisingly, whilst peak usage increased by 18% off-peak usage rose by only 12%. This implies service (point) elasticities of +0.41 and +0.27, respectively; the small response could be because the 7½ mins. frequency was already quite high. It may also be because the service runs for two miles to the town centre carrying long-distance passengers for whom waiting time is a much less important part of generalised costs. In this context, average waiting times were observed to be much less than half the service interval – passengers not arriving at the stops at random but in time to catch a specific bus. They may be a result of the reliability and regularity of the service.

STUDIES OF GENERALISED COSTS AND THE VALUE OF TIME

A considerable amount of research has been undertaken, both in transportation studies and in special studies, into how travellers value savings in travel time. From this work recommended values of time have been derived for use in transportation studies to build up "generalised costs" combining journey times and costs.

The concept of generalised cost provides a useful way of comparing the effects of fare and service changes. Although the value of time will not be the same for all trip purposes, it is possible to say that for a given type of journey a one-penny fare increase will have the same overall effect as an identified increase in waiting time. For example, with a mean fare of 4p and a service interval of 12 mins., an average 1p fare increase represents a 25% fare rise and if the fare elasticity is -0.3 would lead to a $7\frac{1}{2}$% fall in passengers. If the value of time is taken to be 25p ($0.60) an hour and waiting time is valued at $2\frac{1}{2}$ times this rate (i.e. $62\frac{1}{2}$ p an hour) in accordance with standard practice, the 1p fare increase would have an effect equal to an increase in waiting time of just under a minute. This, if waiting time is half the headway, implies a reduction in service frequency to an average of 13.9 mins., a 13.8% decrease, and gives a service elasticity of 0.54. Other values are given in Table II. If we express bus fares and values of time at 1972 prices, average revenue per passenger trip in local authority undertakings was, in fact, rather more than 4p and whilst average service intervals are not

TABLE II

The Service Elasticity Implied by Generalised Costs Equation and Assuming Fare elasticity -0.3

Original Fare	Service Interval (in mins.)	Value of Time Used (in pence per hour) 20p	25p	30p
5p	10	0.31	0.37	0.43
5p	12	0.36	0.43	0.50
5p	15	0.43	0.52	0.61
4p	10	0.39	0.47	0.54
4p	12	0.45	0.54	0.62
4p	15	0.54	0.64	0.74
3p	10	0.57	0.68	0.79
3p	12	0.66	0.79	0.92
3p	15	0.80	0.96	1.11

recorded, we would expect them to be more frequent than 12 mins. in most towns. This would imply that with a fare elasticity of – 0.3, service elasticities should be only about +0.45. Moreover, whereas fare increases are usually made "across the board," operators might be expected to make service reductions in such a way as to minimise ridership losses. The observed service elasticities should be less than this theory would predict.

There is, of course, considerable doubt about appropriate values of time to use, and some evidence that the standard DoE values for evaluation purposes are likely to be below "behavioural" values. However, bus users will generally have lower than average incomes so it is unlikely that 25p ($0.60) an hour is too low a value to adopt. The higher estimates of vehicle mileage elasticity we have identified appear rather inconsistent. They could be the result of unscheduled service cuts which will increase average waiting time much more than would a scheduled cut, or it could be that service cuts, particularly during peak periods have resulted in overcrowding and buses full to capacity. The most likely explanation, however, is that the high values result from the aggregation of journeys of different lengths. Waiting time makes up a much higher proportion of the total journey costs for short trips and their vehicle miles elasticity will be high by comparison with their fares elasticity as Table II suggests. If, as we suspect, short trips are much more sensitive than long trips to changes in generalised costs, then the overall average elasticity will be higher than the simple model suggests. For example, consider a route with a 12 mins. headway, an average fare of 4p and assume that all travellers value their time at 25p per hour. If we divide passengers equally over long trips with an average fare of 5p and short trips with a 3p fare and assume that the long trips have a fare elasticity of – 0.2, which implies a vehicle miles elasticity of +0.29 and the short trips a fare elasticity of – 0.4, which implies a vehicle miles elasticity of +1.05. The average fare elasticity is – 0.3, but the average vehicle miles elasticity would be +0.67 not +0.54 as the simple model suggests. This is an oversimplified example, but considering that we have aggregated over different journey lengths, different routes, different journey purposes, and peak and off-peak periods, service elasticities can be expected to vary widely in individual cases.

Conclusions

Given the crude nature of the variables used and the aggregated nature of the data available, the results are nevertheless very useful. Whilst for each town the limited number of observations available means that standard errors are fairly large, the results all agree with a priori expectations with regard to direction and approximate value and the major differences between towns can be explained by particular characteristics of those towns.

However, these results explain the past and it does not necessarily follow that they can be used to predict the future. As explained, the assumption of constant elasticities is not necessarily correct and the particular circumstances giving rise to these elasticities may have changed, particularly with regard to service. Moreover, these elasticity values are the result of an aggregation of different types of passenger and different types of journey and as we have shown in the previous section, individual vehicle mileage elasticities will vary considerably from the average values we have estimated. Further research is needed into how they actually do vary between peak and off-peak services, short and long journeys, frequent and infrequent services and between scheduled and unscheduled service changes. Until we have greater understanding of this, it would be wrong to use these values to predict the results of any particular service changes.

The research has shown that simple models of bus demand do provide a promising low cost method of forecasting the overall effects of public transport policy measures. Colin Buchanan and Partners are now undertaking further studies combining the use of time series data with more disaggregated cross-sectional data from a home-interview. It is hoped that this will enable forecasts to be made of the patronage effects of alternative changes in the study area's public transport system, and aid quick appraisal of a large number of alternatives. The results for selected plans will be compared with predictions made using the model of a transportation study at present being undertaken by the firm in the same area.

This does not mean that our present results are not useful. They show that, on average, the number of passengers is much more sensitive to service than to fare change and since these are average elasticities, certain types of journey will have much higher elasticities to service cuts. We have attempted to estimate the likely direction of change in these values and whilst different factors work in different directions, it seems likely that ridership will, if anything, probably become more sensitive in future to both vehicle mileage and fare changes. Whilst we certainly would not recommend the use of these values for an individual town, we feel that their use in overall policy issues is valid.

Applying these fare and service elasticities to the decrease in services and rise in fares during the last fifteen years indicates that of the overall decline in passengers of 43% (3.68% per annum), 13.0% was accounted for by vehicle mileage cuts, 14.3% by fare increases beyond the increases of prices in general and only 15.7% was due to the other factors, including rising car ownership and the changing population distribution, that are often blamed for the decline in bus operation. This is supported by evidence of recent trends for other bus operators: between fare increases as the price of bus travel becomes cheaper in relation to other goods the decline in patronage has been halted and in some cases reversed.

Good bus services are clearly the best way to halt declining patronage and are an essential part of any action to restrict car use; raising the cost of car use within limitations will by itself have little effect (Hooper and Mullen, 1974). The fairly high elasticities, particularly for vehicle mileage mean that improved services would themselves generate increased revenue that would go towards meeting the cost of improvement. Subsidies to improve public transport services can bring very substantial social benefits, both in reduced waiting times for existing passengers and in encouraging greater use of public transport.

Secondly, our results suggest that operators and the traffic commissioners have in general placed too much emphasis on keeping fares low rather than on maintaining or improving services. Other available evidence agrees with our results that on average service elasticities are double the size of fare elasticities. Although these average values conceal quite large variations between different groups of bus-users, it is clear that the majority of passengers would be willing to pay much higher fares rather than suffer service cuts. We recognise that low fares are of particular benefit to the least well-off members of the community and so yield additional social benefits, but we feel that social measures of this kind could be financed by a specific subsidy (as are OAP concessions) rather than by imposing a poorer service on all users of public transport.

It has been frequently claimed that, despite this evidence, public transport subsidies should be directed towards reducing fares rather than improving services because, whilst increasing services involves the diversion of additional real measures to public transport, fare subsidies are only a transfer payment and do not involve any resource cost (e.g. Gray and Lewis, 1974). Though this is true, the argument itself is a fallacy; the benefits of lower fares to the bus-user arise only because he is able to purchase additional goods with the money saved. If we allow for the money spent on additional bus travel (which reduces the amount of subsidy required) and for government tax revenues on the alternative purchases, we can see that for a given net cost to the public authorities the real resources consumed in the economy as a whole must be the same. The only difference is the share of resources devoted to public transport.

Appendix A. Advantages and disadvantages of the Logarithmic and Annual Changes Model Forms

Since both vehicle mileage- and fare levels are highly correlated with time, the logarithmic form suffers from a high degree of multicolinearity. This may prevent a proper separation of the individual effects of time, fare changes and vehicle mileage changes. Since changes in fares and service levels took place in different years, this problem does not arise with the percentage form: examination of the data shows fairly low correlation between the fare and service changes.

Since we are explaining the changes in the variables, the effect of random errors will be much more significant as the changes will be small compared with the original values of the variables. This will of course be reflected in the degree of correlation observed. Since we are not explaining the movement of the variable, of which the time trend explained a large part, but only the deviations from the time trend, we can expect the value of R^2 to be much lower. This is not important, it is the standard errors of the coefficients which matter.

Potentially more serious is the question of how we specify the error term. If the errors take the form of a once and for all change in passengers (as they would if there is some unmodelled permanent change in the service pattern, such as the introduction of one-man operation, or if the rise in car ownership is not at a constant annual rate, but varies from year to year) then the logarithmic form would suffer from serial correlation of error.

If on the other hand the main kind of errors were factors affecting just one year (such as a strike for example), the percentage changes form would suffer from serial correlation. We would expect that the first kind of error would predominate, but in any case we can check for serial correlation by using the Durbin–Watson test on the observed residuals.

The two approaches weight the observations rather differently. A least-squares method places the greatest weight on the observations farthest from the mean. In the case of the logarithmic form this means greatest weight is on the first and last years, which may be atypical of the rest of the period. The percentage changes method however will place most weight on the greatest percentage changes, thus minimizing the effects of random errors. This however will affect only the time trend which should be treated cautiously as it may be biased by errors in the estimation of fare and service elasticities.

Appendix B. A Note on the Estimates for Leeds

In the case of Leeds the original regression gave the result

$$\hat{P} = -0.13339 + \underset{(0.38113)}{0.25839\,\hat{V}} - \underset{(0.11601)}{0.39830\,\hat{F}} \tag{13}$$

Not only was the standard error of vehicle mileage large but a plot of the unexplained residual variation in each year against changes in vehicle mileage showed a strong relationship (Fig. 2) except in the final two years. It is clear that the effect of vehicle mileage in the first ten years was much greater than the original equation suggests but because the last two years were those where vehicle mileage fell it gave a much lower vehicle mileage elasticity estimate. The change in the last two years may well be associated with the vehicle mileage cuts. Since service cuts are presumably undertaken to minimise passenger lòss whilst service increases are undertaken in such a way as to maximise passenger gains, there is no reason to expect the elasticities with respect to services increases to be the same as the elasticities to service cuts. However the change could be due to factors not modelled. It was not possible to determine which of these was the cause, and therefore these changes were modelled by the inclusion of a dummy variable. The coeffi-

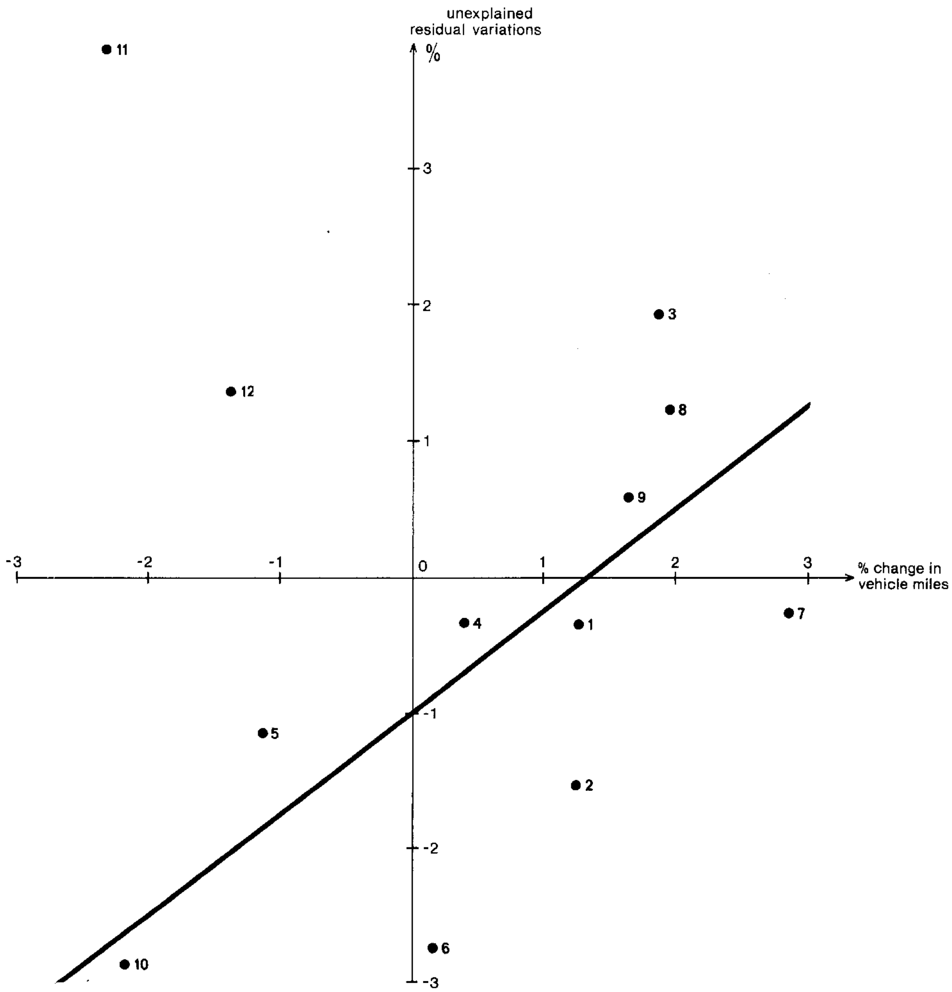

Fig. 2. Leeds – plot of unexplained residual variations against changes in vehicle miles.

cient of this variable took the value 5.2, indicating that the unknown changes caused an average increase in passengers of 5.2% above that which the model predicted: this appears much too large to be explained by changes in the vehicle mileage elasticity alone – passengers have been increasing despite both rising fares and reductions in vehicle mileage. Therefore the Leeds results must be treated with caution, and the vehicle mileage elasticity can only be taken to refer to the first nine years of the twelve years considered.

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