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The Demand for Local Bus Services in England

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Abstract

This paper examines the demand for local bus services in England. The study is based on a dynamic model relating *per capita* bus patronage to bus fares, income, and service level, and is estimated using a combination of time-series and cross-section data for English counties. The results indicate that patronage is relatively fare-sensitive, with a wide variation in the elasticities.

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Introduction

This paper investigates the demand for local bus services in England. It is based on a project carried out for the Department of the Environment, Transport and the Regions (DETR)[1] in the UK. The main objective of the study has been to obtain estimates of fare elasticities that could be used in policy calculations to project the change in bus patronage nationally as a result of a given "average" fare change, and to explore possible variation in the elasticity.

Basically, two approaches can be used to estimate the fare elasticity, dependent on the type of data utilised. The first relies on actual data on bus patronage; the second on stated preference surveys. Recently, there have been many studies using stated preference methods which, when real data are impossible or difficult to obtain, can prove indispensable. However, such methods have their limitations and the results are often difficult to interpret. They also require extended — and costly — data collection. The present analysis is thus entirely based on actual patronage data.

In judging the impact of a given change in bus fares, it is essential to define the time perspective concerned. In recent years two quite different methods have been used to make such a distinction. The first is to define, *a priori*, certain classes of behavioural response as "short-term" and others as "long-term". In principle this enables cross-section models to be interpreted as indicating something about the time scale of response, by consideration of which responses are included. The conditions for this to be valid are stringent and rarely fulfilled, and even where they are, no statements are possible about how many months or years it takes for the long-term effect to be completed. The second approach is to use time-series data with a model specification in which a more or less gradual response over time is explicit, the time scale being determined empirically as one of the key results of the analysis. Methodologically, this method is far superior. It also has another advantage: for policy purposes it is necessary to know not only the level of the response in the "long run", but also *how long* the adjustment takes. This can only be achieved on the basis of dynamic models that explicitly take into account the effects of fares and other relevant factors in different time perspectives. Such an analysis requires observations of changes in bus patronage, fares, and so on, over time. The approach taken in this study is to employ a dynamic methodology to investigate the response to fare changes over time.

[1] As a result of a departmental reorganisation in 2001, transport is now part of the Department of Transport, Local Government and the Regions (DTLR).

The estimation of bus fare elasticities is based on annual operators' data for years 1986 to 1996 on bus patronage, fares, and other relevant factors influencing bus use, which have been obtained from the DETR. The data for the individual operators are aggregated to county level, and combined with information on income and population for the individual counties.

The fare elasticities are estimated on the basis of dynamic econometric models relating *per capita* bus patronage (all journeys) to real *per capita* income, real bus fares (average revenue per journey), service level (bus vehicle kilometres), real motoring costs, and demographic variables. The dynamic methodology employed distinguishes between the short- and long-term impacts of fare changes on bus patronage, as well as providing an indication of the time required for the total response to be complete.

The next section describes the county-level data used for the analysis. The econometric model is presented in the next section, followed by statistical estimates and elasticities. The paper ends with some concluding remarks.

Bus Patronage, Fares, and Service

The data used for the analysis were obtained from the *STATS100A* database provided by the DETR. This database includes financial year returns to the DETR from bus operators licensed for 20 or more vehicles. It contains information on vehicle miles, passenger receipts, passengers carried, number of vehicles and staff, and (for operators of local services) concessionary fare contributions, public transport support, and fuel duty rebate. In addition, operators are also asked to estimate a breakdown, by county, of passenger journeys and receipts, revenue support, concessionary fare contributions, and vehicle miles, as well as information on operating and administrative expenditure, depreciation, and profitability. These data have been collected in this form since the 1986 deregulation of bus services outside London. Permission was sought from the large bus operators in Great Britain (that is, those with a fleet size of 50 or more) to have access to their returns to the DETR.

The data used in this study are for the operators in England who gave permission to use the information contained in the database. These make up 87 per cent of bus vehicle kilometres and 93 per cent of passenger journeys in England. The operator data was aggregated to the county level, resulting in 46 counties for the financial years 1987/88 to 1996/97. For simplicity, these are referred to as 1987 to 1996.

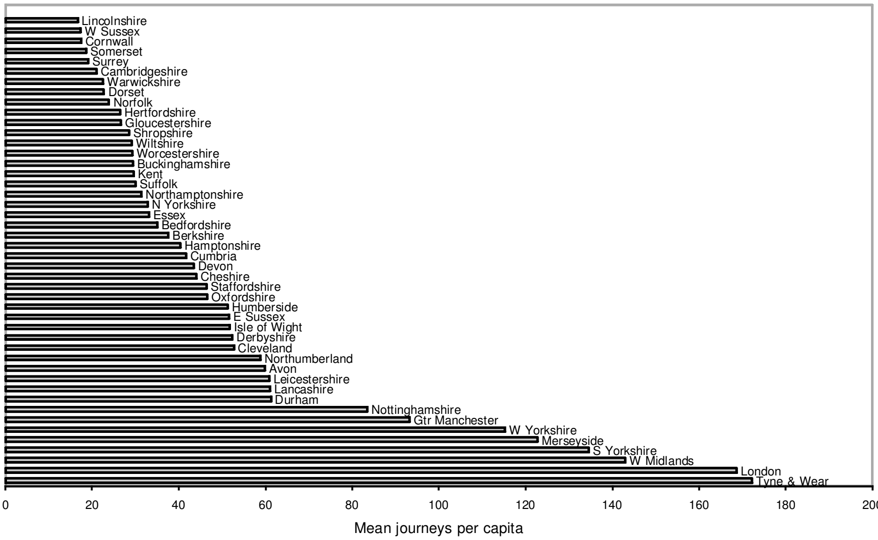
The data on bus patronage, fares, and service for each county were combined with county level information on population and disposable income, obtained from *Regional Statistics.*

Bus patronage

The data on bus patronage includes all trips, both full-fare and concessionary. Figure 1 shows average bus journeys *per capita* for the period 1987 to 1996 on a county level. The variation is apparent, ranging from over 170 journeys in Tyne and Wear to around 20 in Lincolnshire. Of the metropolitan counties, Greater Manchester has the lowest *per capita* bus use — about half that of Tyne and Wear and London. Clearly, the metropolitan areas show the most intensive bus use, followed by Nottinghamshire, Durham, Lancashire and Leicestershire. The majority of counties show an average bus use of between 20 and 60 journeys *per capita*. In general, the

Figure 1

Bus journeys per capita *in English counties. Average 1987–96.*



more densely populated counties have a more intensive bus use. There are a number of exceptions, however. For example, the densely populated counties around London — Surrey, Berkshire, and Hertfordshire — have

relatively low bus use, while sparsely populated Northumberland has a comparatively high *per capita* patronage.
As is the case for Great Britain as a whole, bus use has been declining over the past decade in most English counties. During the period 1986–1996, the average decline was approximately 20 per cent. Only Oxfordshire has shown a continual increase in patronage.

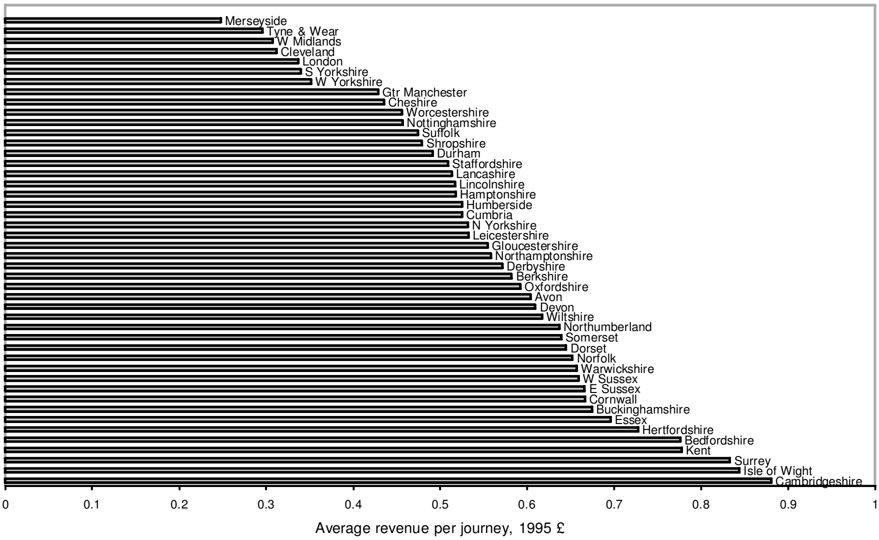
Bus fare

Since the *STATS100A* database provides no information on fares, these have to be calculated on the basis of data on revenues and journeys. There are two alternatives: passenger receipts including or excluding concessionary fare reimbursement (CFR). By including CFR we obtain an approximate measure of the average non-concessionary fare; that is, fare without concessions. Excluding the CFR gives a measure of the average fare actually paid by all bus patrons. Since the patronage data include concessions as well as full-fare-paying patrons, this latter fare definition is the more appropriate, and it allows for a changing mix of passenger categories. The fare variable is thus calculated as real average revenue per passenger journey excluding concessionary fare reimbursement.

The average fares, calculated in this manner, for each of the counties over the period are shown in Figure 2. The considerable variation amongst

Figure 2

Bus fares in English counties, 1995 £ per journey. Average 1987–96.



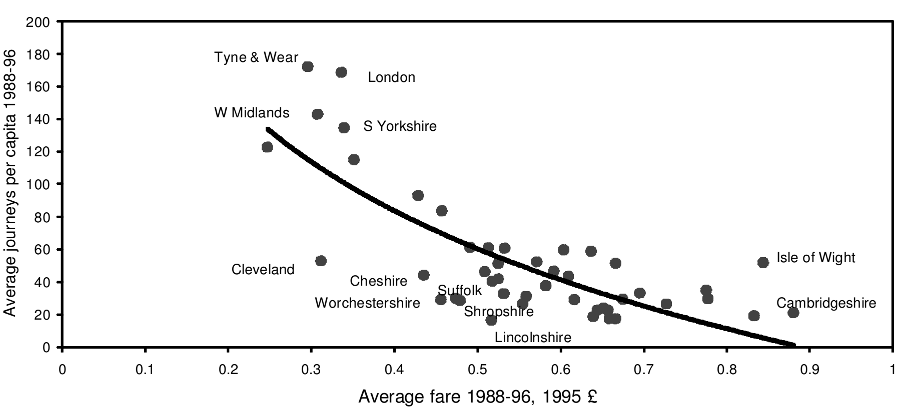
counties is apparent — from 22 pence per journey in Merseyside to 88 pence in Cambridgeshire. Fares are, on average, considerably lower in the more urban counties — London, the six former Metropolitan counties of England, and Cleveland, than in the more suburban and rural counties.

In general, the counties with the lowest fares have the most favourable concessionary schemes. The counties with the lowest fares — London, the Metropolitan counties and Cleveland — have a very high proportion of CFR, while those with the highest fares — Cambridgeshire, Surrey, Isle of Wight, Kent and Bedfordshire — have a low proportion of CFR. There are a few obvious exceptions: Cheshire, for example, has a relatively low fare, but also a low proportion of CFR. There is substantial variation in the proportion of concessionary fare reimbursement across counties, from 40 per cent in Merseyside to 0 per cent in Bedfordshire. In the majority of counties, CFR is well under 20 per cent of total receipts. The only exceptions are the former Metropolitan counties, and Cleveland and Suffolk.

In real terms, average revenue has gone up in most English counties since deregulation in 1986. In about 10 per cent of counties the increase was over 40 per cent. On average, the increase was about 20 per cent. The greatest fare increases are noted for Cleveland and South Yorkshire. In a few counties — Cumbria, Norfolk and West Midlands — fares have remained more or less constant over the period, and only in one county (Oxfordshire) have fares actually fallen.

Figure 3

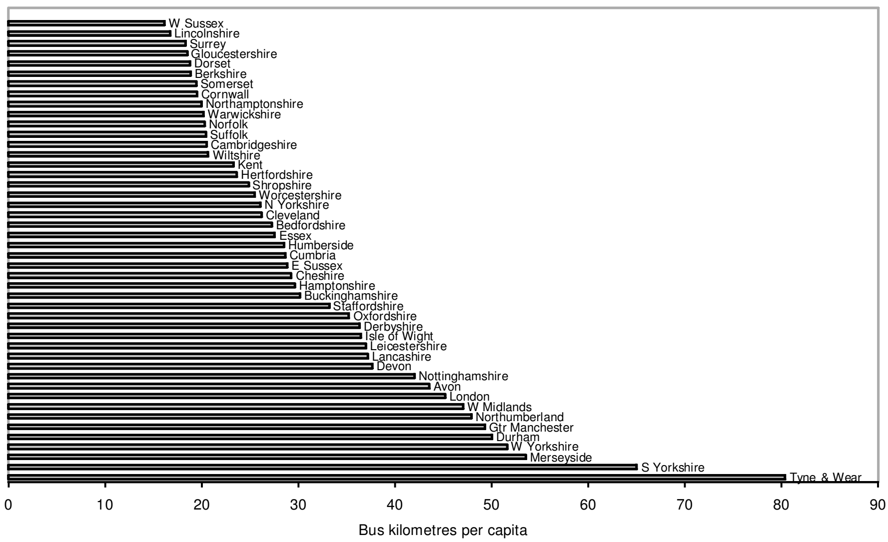
Relationship between average fares and bus patronage in English counties, 1987–96.



The relationship between average fares and journeys *per capita* is illustrated in Figure 3. There does appear to be a negative relationship — although not a linear one — between patronage and fare level. A number of counties, however, show a significant deviation from the "best-fit" line. Particularly, patronage is higher in Tyne & Wear, London, and the Isle of Wight than would be suggested by their fare levels. Similarly, patronage is lower in Cleveland, Cheshire, Worcestershire, Lincolnshire, Suffolk, and Shropshire.

Figure 4

Bus kilometres per capita *in English counties. Average 1987-96.*



Service

Bus vehicle kilometres *per capita* is used as the proxy for level of service. The large variation among the counties is illustrated in Figure 4. Tyne & Wear has the highest service intensity and West Sussex the lowest. In general, the most densely populated counties have better bus service than more rural counties. Overall, bus vehicle kilometres tend to be higher in the six former Metropolitan counties of England than elsewhere in the country. Again this is not very surprising.

In most counties, bus service has been increasing over the past 10 years. The greatest percentage increases are in Cleveland, Surrey, Oxfordshire, Gloucestershire, and Bedfordshire — well over 40 per cent in all cases.

Buckinghamshire, Hertfordshire, and Derbyshire show the greatest decline. For most other counties, service has increased by less than 20 per cent.

The Model

Because of the aggregate nature of the available data, a relatively simple model is used to model bus patronage. We assume that the long-run equilibrium demand for bus services, in terms of journeys *per capita*, Q^*_{Rt}, in county R in year t can be expressed as a function f of the bus fare, F_{Rt}, the service level, S_{Rt}, *per capita* disposable income, I_{Rt}, demographic factors, D_{Rt} (population density, the percentage of pensioners in the population), and the cost of alternative modes. For the latter, we assume that the only viable substitute for bus travel is car use, so the cost of alternative modes is represented by motoring costs. However, as these are not available on a county level, national data[2] are used, so that motoring costs, M_t, vary over time but are assumed to be the same for all counties.[3]

$$Q^*_{Rt} = f\left(F_{Rt}, S_{Rt}, I_{Rt}, M_t, D_{Rt}\right). \tag{1}$$

In estimating the demand model, we assume that all explanatory variables are given or determined exogenously. Although the service variable (bus kilometres *per capita*), can also be seen as a measure of supply, which itself is determined by demand, we assume that supply in any given year is unaffected by demand changes within the same year. This may be a strong assumption, and it would be preferable to estimate the complete supply–demand system.

In order to account for lags in the adjustment to changes in the explanatory variables, a partial adjustment model[4] is used to relate actual patronage, Q_{Rt}, to its long-run equilibrium level. This results in the following model:

$$Q_{Rt} = f(F_{Rt}, S_{Rt}, I_{Rt}, M_t, D_{Rt}) + \theta_R Q_{Rt-1} \tag{2}$$

where $0 \leq \theta_R < 1$. The adjustment coefficient, $1 - \theta_R$, indicates the proportion of the gap between equilibrium and actual patronage that is closed each year. The presence of demand in the previous period on the right-

[2] The index of total motoring costs, obtained from the DETR, includes all running costs as well as car purchase costs.

[3] Although there may be some differences in the cost of motoring among counties, it is not unreasonable to assume that development over time is similar.

[4] Dargay and Hanly (1999) use both partial adjustment and error-correction models for aggregate GB data. However, the time period available for the county data is too short to apply cointegration tests.

hand side of the equation can be interpreted in terms of habits or inertia — what individuals do in the past also affects their future behaviour. Also, since demand in period $t-1$ is influenced by prices and so on in period $t-1$, and similarly for all other previous periods, demand in any period is determined by the entire past history of prices and other relevant variables. Individuals do not respond to changing circumstances instantaneously, but with a delay.

Assuming f to be a linear function and all variables to be in logarithmic forms results in the following constant elasticity specification:

$$\begin{aligned} \mathrm{Ln}Q_{Rt} = {} & \alpha_R + \beta_{FR}\mathrm{Ln}F_{Rt} + \beta_{SR}\mathrm{Ln}S_{Rt} + \beta_{IR}\mathrm{Ln}I_{Rt} \\ & + \beta_M \mathrm{Ln}M_t + \beta_{DR}\mathrm{Ln}D_{Rt} + \theta_R \mathrm{Ln}Q_{Rt-1} \end{aligned} \tag{3}$$

The short-run elasticities are obtained directly from the coefficients of the independent variables, while the long-run elasticities are calculated as the short-run elasticities divided by the adjustment coefficient $(1-\theta)_R$. The greater the value of θ_R, the slower the speed of adjustment and the greater the difference between the short- and long-run elasticities.

In the specification shown above, the elasticities are constant and independent of the levels of the independent variables. An alternative specification, which allows the fare elasticity to be related to the fare level, can be written as:

$$\begin{aligned} \mathrm{Ln}Q_{Rt} = {} & \alpha_R + \beta_{FR}F_{Rt} + \beta_{SR}\mathrm{Ln}S_{Rt} + \beta_{IR}\mathrm{Ln}I_{Rt} \\ & + \beta_M nM_t + \beta_{DR}nD_{Rt} + \theta \mathrm{Ln}Q_{Rt-1} \end{aligned} \tag{4}$$

Here, the short-run fare elasticity is equal to $\beta_{FR}F_{Rt}$ and the long-run elasticity equal to $\beta_{FR}F_{Rt}/(1-\theta_R)$, so that both elasticities vary over time and increase with the fare level. Since this model has the same dependent variable as the constant elasticity model, the choice between them can be made on the basis of simple statistical tests.

Equations (3) and (4) can be estimated separately for each county, so that county-specific fare, income, and service elasticities can be obtained. However, given the short time period for which we have data — 10 annual observations — such an approach would not provide reliable estimates of the model parameters. For this reason, the model is estimated by pooling the time-series data for the individual counties. By combining the data in the estimation procedure, the number of observations (and degrees of freedom) is increased, thus improving the significance of the estimated parameters. It also provides more variation in the data, since patronage and fares vary more between counties than over time. The disadvantage of this technique, however, is that it assumes that the demand relationship and the elasticities are the same for all counties. In pooling, differences between regions that are not captured in the included explanatory variables can be assumed to be either fixed or random. In the Fixed Effects Model, differences between counties can be represented by county-specific intercepts (α_R). The Random Effects Model, on the other hand, represents the differences between regions as differences in the random error term. There is no *a priori* manner of choosing which specification is the more appropriate, and the choice must be based on statistical tests. The following discussion is based on a Fixed Effects Model, although both Fixed and Random Effects specifications were estimated.[5]

In the empirical work, we estimate two forms of the pooled model. In the most restricted form, it is assumed that all slope coefficients (the βs and θ) are the same for all counties and that differences between counties can be represented by county-specific intercepts (α_R):

$$\begin{aligned} \mathrm{Ln}Q_{Rt} = \alpha_R + \beta_F \mathrm{Ln}F_{Rt} + \beta_S \mathrm{Ln}S_{Rt} + \beta_I \mathrm{Ln}I_{Rt} \\ + \beta_M \mathrm{Ln}M + \beta_D \mathrm{Ln}D_{Rt} + \theta \mathrm{Ln}Q_{Rt-1} \end{aligned} \tag{5}$$

For the constant elasticity model above, the elasticities are the same for all counties. For the variable fare elasticity model in (4), the fare elasticity is dependent on the fare level, so that it will vary amongst counties inversely in relation to their fares.

The second model also allows the coefficient of the fare variable (or the fare elasticity, in the constant elasticity model) to be region specific:

$$\begin{aligned} \mathrm{Ln}Q_{R,t} = \alpha_R + \beta_{FR} \mathrm{Ln}F_{Rt} + \beta_S \mathrm{Ln}S_{Rt} + \beta_I \mathrm{Ln}I_{Rt} \\ + \beta_M \mathrm{Ln}M_t + \beta_D \mathrm{Ln}D_{Rt} + \theta \mathrm{Ln}Q_{R,t-1} \end{aligned} \tag{6}$$

where β_{FR} is the coefficient relating to the fare variable for county R, α_R is the county-specific intercept term, and all other coefficients are constrained to be equal for all counties. For the constant elasticity model above, the fare elasticity can vary among counties, but will be the same for each county over time and for all fare levels. For the variable elasticity model, the fare elasticity will vary both among counties as well as over time for each county, dependent on the fare level. Model (5) is a restricted form of model (6), that is, with $\beta_{FR} = \beta_F$ for all counties. This can be tested using a simple statistical test.

[5] Using a Hausman Test to test between the Fixed and Random Effects specifications results in test statistics of 29.9 and 30.7 for the constant and variable elasticity model, respectively, clearly rejecting the Random Effects specification in preference to the Fixed Effects.

Model Estimation

The four variants of the model described in the previous section were estimated from the combined time-series cross-section data for English counties. The natural logarithm of bus journeys *per capita* is the dependent variable for all the estimations. The fare and service variables are as described in the previous section. Income is defined as household disposable income *per capita*, motoring costs as the national index, and all price and income variables are converted to 1995 prices using the Retail Price Index. Initially, two demographic variables were included: population density, and the percentage of pensioners in the county.[6] However, as population density was not found to be significant in any of the specifications, the models presented below exclude this variable.[7]

Since a lagged dependent variable is included among the regressors, the first observation is lost for each county, so that we have nine annual observations for each of the 46 counties, a total of 414 observations.

Two specifications are estimated — one constraining all coefficients to be the same across counties, and one in which the coefficients of the fare variable, and thus the price elasticity, are county-specific. In addition, for each of the specifications (constrained and unconstrained) two different functional specifications are estimated: (a) a "constant elasticity" model in which *all* variables are specified in natural logarithms, and whose coefficients yield the elasticities of interest directly; and (b) a model in which all variables are in natural logarithms *except* the price (fare) variable, which is specified in level terms. In the latter, the elasticity is not constant but increases with the price level (bus fare).

The estimated parameters (with the exception of the county-specific intercept terms) for the constrained models are reported in Table 1 and for the unconstrained model in Table 2. In all cases, the models fit the data well, with adjusted R-squared values very near one and the F-tests for the fixed effects confirming the importance of individual intercepts. The estimated coefficients are generally of the expected signs — income and the bus fare have negative effects on bus patronage, whereas service, motoring costs and the percentage of pensioners have a positive influence. The coefficients of income, service, motoring costs, the percentage of pensioners, and the lagged patronage variable are nearly identical in both constrained models, as they are in both unconstrained models. However,

[6] Income, population, and the number of pensioners on a county level were obtained from Regional Statistics.

[7] As population density varies little over time, its effects are captured in the county-specific intercept terms.

comparing the constrained models with the unconstrained, we see that the coefficients of income, motoring costs, and percentage of pensioners are greater in absolute value in the unconstrained models. Adjustment appears to be quicker in the unconstrained model, with 58 per cent of total adjustment occurring within one year, as opposed to 48 per cent in the constrained models. All estimated coefficients, with the exception of the percentage of pensioners, are highly significant in the constrained models (Table 1), while the fare coefficients are significant for slightly less than half the 46 counties in the unconstrained model (Table 2). The poor significance of the fare coefficients in the unconstrained model (only 21 of the 46 fare coefficients are significant at the 5% level) is a result of the small number of observations on which the county-specific estimates are based.

Table 1
Constrained Model Estimates

Dependent variable: Journeys *per capita*, 414 observations

Variable	*Constant Fare Elasticity* *Coefficient*	*T-Statistic*	*Variable Fare Elasticity* *Coefficient*	*T-Statistic*
Journeys(-1)	**0.52**	10.10	**0.52**	10.33
Income	**–0.39**	–3.14	**–0.39**	–3.24
Service	**0.49**	5.99	**0.47**	5.95
Motoring Costs	**0.32**	3.87	**0.35**	4.33
Percent Pensioners	**–0.08**	–0.54	**–0.01**	–0.10
Fare	**–0.33**	–4.87	**–0.74**	–6.79
Adjusted R-squared	0.9998		0.9998	
SSE	1.9113		1.8246	
Log Likelihood	525.8225		535.4312	
F-test: Fixed Effects	4.26 ($P = 0.000$)		4.70 ($P = 0.000$)	

Note: coefficients in bold type are significant at the 95% level.

The statistical tests for model selection are shown in Table 3. The first set of tests shown concern the functional relationship between patronage and fares; that is, the constant *versus* the variable elasticity formulations.[8] For both the model with common fare coefficients (constrained) and the model with county-specific fare coefficients (unconstrained), the variable elasticity (semi-log) specification is the one preferred. The fare elasticity is thus not constant, but depends on the fare level. In the second set of tests, the hypothesis of common fare coefficients is tested against county-specific fare coefficients.[9] For both the constant and variable elasticity models, the

[8] Based on a Likelihood Ratio Test of the Likelihood values of the respective models.
[9] Based on an F-test comparing the SSE of the restricted and unrestricted models.

Table 2
Unconstrained Model Estimates: County Specific Fare Elasticity

Dependent variable: Journeys *per capita*, 414 observations

Variable	*Constant fare elasticity* *Coefficient*	*T-Statistic*	*Variable fare elasticity* *Coefficient*	*T-Statistic*
Journeys(-1)	**0.42**	6.63	**0.42**	6.63
Income	**−0.57**	−4.16	**−0.60**	−4.40
Service	**0.48**	5.19	**0.49**	5.25
Motoring Costs	**0.65**	7.17	**0.65**	7.41
Percent Pensioners	**0.44**	2.64	**0.49**	2.91
Fare: Northumberland	−0.06	−0.02	−0.09	−0.02
Cumbria	−0.55	−0.80	−1.08	−0.78
Durham	0.04	0.07	0.05	0.04
Tyne & Wear	**−0.45**	−4.39	**−1.54**	−4.79
Cleveland	0.06	0.26	0.15	0.18
North Yorkshire	−0.24	−0.38	−0.44	−0.35
Lancashire	0.00	0.01	0.02	0.04
West Yorkshire	**−0.39**	−4.17	**−1.04**	−3.90
Humberside	**−1.21**	−10.95	**−2.08**	−13.32
South Yorkshire	**−0.67**	−5.90	**−1.94**	−5.57
Merseyside	0.21	1.03	0.81	0.98
Manchester	**−0.52**	−5.37	**−1.15**	−5.25
Cheshire	−0.38	−0.65	−0.90	−0.75
Derbyshire	−0.34	−1.56	−0.57	−1.55
Nottinghamshire	**−0.43**	−2.99	**−0.92**	−3.00
Lincolnshire	−0.22	−0.34	−0.53	−0.40
Staffordshire	−0.64	−1.43	−1.23	−1.43
Shropshire	−0.01	−0.02	0.02	0.02
Leicestershire	**−0.48**	−2.70	**−0.89**	−2.77
Norfolk	**−1.64**	−3.40	**−2.54**	−3.59
West Midlands	**−1.54**	−9.02	**−4.98**	−9.04
Worcestershire	**−0.71**	−2.17	**−1.62**	−2.24
Warwickshire	−0.16	−0.46	−0.22	−0.44
Northamptonshire	−0.44	−1.21	−0.79	−1.25
Cambridgeshire	**−1.00**	−3.54	**−1.13**	−3.58
Suffolk	−0.30	−0.79	−0.65	−0.81
Gloucestershire	−0.01	−0.01	−0.03	−0.02
Oxfordshire	**−0.49**	−2.72	**−0.92**	−3.40
Buckinghamshire	−0.31	−0.75	−0.43	−0.78
Bedfordshire	−0.53	−1.20	−0.70	−1.27
Hertfordshire	**−0.50**	−2.20	−0.67	−1.90
Essex	−0.13	−0.53	−0.19	−0.54
Avon	**−0.69**	−2.93	**−1.11**	−2.83
Wiltshire	−0.30	−0.54	−0.45	−0.50
Berkshire	**−0.49**	−2.37	**−0.85**	−2.63
London	**0.28**	3.69	**1.04**	4.19
Cornwall	−0.51	−1.28	−0.77	−1.27
Devon	**−0.91**	−1.89	**−1.55**	−1.97
Somerset	1.48	0.50	2.40	0.52
Dorset	−0.19	−0.31	−0.34	−0.35
Hampshire	**−0.79**	−5.57	**−1.47**	−5.70
Surrey	**−1.15**	−3.17	**−1.49**	−3.33
Kent	**−0.68**	−4.42	**−0.86**	−4.53
West Sussex	−0.32	−0.26	−0.53	−0.29
East Sussex	**−0.80**	−2.94	**−1.19**	−2.90
Isle of Wight	−0.66	−0.80	−0.76	−0.76
Adjusted R-squared	0.9998		0.9998	
SEE	1.4311		1.4143	
Log Likelihood	585.7099		588.1617	
F-test Fixed Effects	2.57 ($P = 0.000$)		3.07 ($P = 0.000$)	

Note: coefficients in bold type are significant at the 95% level.

Table 3
Tests for Various Model Formulations

	Test	*Probability*	*Conclusion*
Tests for variable versus constant elasticity			
Common fare coefficients	$\chi^2 = 19.2$	Prob. = 0.00	Reject constant elasticity model
County-specific fare coefficients	$\chi^2 = 4.90$	Prob. = 0.03	Reject constant elasticity model
Tests for common fare coefficients	*SSE*		
Constant elasticity model	$F = 2.36$	Prob. = 0.00	Reject common fare coefficients
Variable elasticity model	$F = 2.04$	Prob. = 0.00	Reject common fare coefficients

constrained versions are rejected in favour of the unconstrained formulations, implying that the fare elasticity is not the same for all counties. In summary, the statistical tests favour the unconstrained variable elasticity model, implying that fare elasticity both varies among counties and increases with the level of fare. This implies that the variation in fare elasticities among counties is not solely explained by differences in fares.[10]

The resulting elasticities for the four model specifications are shown in Table 4. The first two rows report the elasticities for the constrained and unconstrained versions of the constant elasticity model. The fare elasticity shown for the unconstrained model is the average of the elasticities estimated for the individual counties. The next set of results is for the variable

Table 4
Estimated Short-run (SR) and Long-run (LR) Elasticities Based on Pooled Data for English Counties

	Fare		*Income*		*Service*		*Motoring Costs*		*% Pensioners*	
	SR	LR	SR	LR	SR	LR	SR	LR	SR	LR
Constant elasticity										
Constrained	−0.33	−0.68	−0.39	−0.82	0.49	1.03	0.32	0.66	(−0.08)	(−0.17)
Unconstrained*	−0.43	−0.74	−0.57	−0.98	0.48	0.83	0.65	1.12	0.44	0.75
Variable elasticity										
Constrained			−0.39	−0.81	0.49	0.83	0.35	0.72	(−0.01)	(−0.03)
Minimum fare = 17p	−0.13	−0.26								
Average fare = 56p	−0.41	−0.86								
Maximum fare = £1	−0.74	−1.53								
Unconstrained*			−0.60	−1.02	0.42	0.79	0.65	1.12	0.49	0.85
Minimum fare = 17p	−0.13	−0.23								
Average fare = 56p	−0.44	−0.75								
Maximum fare = £1	−0.79	−1.35								
Aggregate GB	−0.33	−0.62	0.41	−0.80			Not estimated			

*average of individual elasticities for all counties (...) elasticities not significantly different from zero.

[10] This is a slightly different result from that obtained in Dargay and Hanly (1999) using a specification which excluded motoring costs and the percentage of pensioners.

elasticity model. In the constrained model, the fare elasticity is dependent on the fare level, and the fare elasticities shown in the table are calculated at the minimum, average, and maximum fare (in 1995 £) for all counties over the observation period. For the unconstrained model, the fare elasticity varies by county as well as by fare level. The elasticities shown are the averages of the elasticities for the individual counties calculated at the same minimum, average, and maximum fares. The "average fare" elasticities are very similar in both specifications, and they are also close to the average elasticity in the unconstrained constant elasticity model. For the other variables, the major differences in the elasticities occur between the constrained and unconstrained versions. The income elasticity is slightly more negative in the unconstrained models, the service elasticity slightly smaller, and the impact of motoring costs and the percentage of pensioners greater. As the statistical tests favour the unconstrained variable elasticity model, the elasticities resulting from this specification are those preferred.

For comparison, the elasticities obtained in Dargay and Hanly (1999) from the aggregate GB data using the same fare variable are shown in the table. We would expect the results to be roughly similar. However, we would not expect the results to be perfectly identical since the present data set is slightly less inclusive than that used for the aggregate models, leaving out as it does those operators with a fleet size of less than fifty vehicles, which account for approximately 15 per cent of national passenger receipts. Also, the aggregate GB estimates are based on a much longer observation period. Despite this, the resulting elasticities are not very different.

The unconstrained models allow us to calculate separate fare elasticities for each county. These range from 0 (not statistically different from 0) to −1.6 in the short run and −3.0 in the long run. Clearly, these elasticities must be interpreted with caution, based as they are on so few data observations. At best they give an indication of the wide range in which the fare elasticity can fall in specific areas.

The variable fare elasticity model also results in different elasticities for individual counties. As shown in Figure 2 above, the mean fare over the period for the individual counties ranges from 25 pence per journey in Merseyside to nearly 90 pence in Cambridgeshire. For the variable elasticity model, the average elasticities for the individual counties will show a similar range of variation. The long-run elasticities for the individual counties, calculated at the mean fare in each county over the 1987–1996 period, range from −0.4 in Merseyside to −1.4 in Cambridgeshire, with the majority of counties lying in the region of −0.7 to −1.1.

In order further to investigate differences in fare elasticities between urban and less urban areas, separate models were estimated for the Shire counties and the Metropolitan areas. These are reported in Table 5, and

Table 5
Model Estimates, Constant Elasticity Model: Common Fare Elasticity. English Shire Counties and Metropolitan Counties (excluding London) Estimated Separately

Dependent variable: Journeys *per capita*

	Shire counties 39 counties 351 observations		*Metropolitan counties 6 counties 54 observations*	
Variable	Coefficient	*T*-Statistic	Coefficient	*T*-Statistic
Journeys(-1)	**0.26**	5.29	**0.51**	5.77
Income	**−0.43**	−3.49	**−1.26**	−5.80
Service	**0.72**	11.43	**0.36**	3.89
Motoring Costs	−0.17	−0.85	**0.34**	1.81
Percent Pensioners	**0.73**	1.96	**−1.15**	−2.20
Fare	**−0.49**	−7.72	**−0.26**	−3.52
Mean Fixed Effect	2.48	1.41	**13.61**	4.98
Adjusted R-squared	0.9666		0.9832	
SSE	1.9881		0.0372	
Log Likelihood	409.9207		119.9333	

Note: coefficients in bold type are significant at the 95% level.

Table 6
Estimated Short-Run (SR) and Long-Run (LR) Elasticities for English Shire Counties and Metropolitan Areas

	Fare		*Income*		*Service*		*Motoring Costs*	
	SR	LR	SR	LR	SR	LR	SR	LR
Metropolitan areas	−0.26	−0.54	−1.26	−2.58	0.36	0.73	0.34	0.69
Shire counties	−0.49	−0.66	−0.43	−0.58	0.72	0.97	(−0.17)	(−0.23)

Note: Elasticities in parenthesis are not significantly different from zero.

the resulting elasticities presented in Table 6. Both the fare and service elasticities are higher in the Shire counties than in the Metropolitan areas, while the opposite is the case for the elasticity with respect to motoring costs. These results are not unreasonable. Bus fares and service provision will have more of an effect in rural areas than in urban areas, because car use is less advantageous in urban areas given congestion, parking, and so on. Motoring costs have less of an effect on bus patronage in rural areas because bus use is a less viable alternative for many car trips than it is in urban areas with better bus services. Finally, income has a greater negative effect on bus use in urban areas. This is contrary to expectations given the relative advantage of motoring in rural areas, but may reflect the fact that car ownership is closer to saturation in rural areas, so that increasing income has a greater effect on car ownership and thus a greater negative impact on bus use in urban areas.

Conclusions

The econometric results presented above suggest that the most likely values of the fare elasticity for England as a whole are around −0.4 in the short run and −0.9 in the long run. The evidence suggests that the long-run elasticities are about twice the short-run elasticities.

Models with separate fare elasticities for each county are statistically preferred to specifications in which the fare elasticity is constrained to be equal for all counties. The results of the unconstrained models show a considerable variation in the fare elasticity across counties — a range from 0 to over −3.0 in the long run.

There is statistical evidence that demand is more price-sensitive at higher fare levels. This conclusion is drawn on the basis of models in which the fare elasticity is related to the fare level. The variation in the elasticity ranges from −0.1 in the short run and −0.2 in the long run for the lowest fares (17 pence in 1995 prices) to −0.8 in the short run and −1.4 in the long run for the highest fares (£1 in 1995 prices).

Separate estimates of the fare elasticity for the Shire counties and the Metropolitan areas (excluding London) indicate that patronage in the former is on average more sensitive to fare changes than in the latter, and significantly so. The less-elastic demand in the Metropolitan areas can be explained in terms of their urban characteristics, better bus service provision, and lower fares.

The measure of service quality used in this study is *per capita* bus kilometres for the market considered. Clearly, this is a very crude approximation for the many factors that make up the quality of a bus service. It is, however, the only feasible measure on the aggregate level, and the one most commonly used in such studies. In general, the estimated service elasticities are the same order of magnitude as, or slightly larger than, the fare elasticities, although opposite in sign. This suggests that an increase in fares combined with an increase in service would leave demand unchanged. For example, if fares were increased by 10 per cent and the number of vehicle kilometres also increased by 10 per cent, patronage would remain approximately the same as previously.

All the evidence is in agreement regarding the sign of the income elasticity — it is negative in the long run, suggesting bus travel to be an inferior good. This is in agreement with most other studies.[11] The negative long-run elasticity reflects the effect of income through its positive effect on car ownership and use, and the negative effect of the latter on bus patronage. It should be stressed, however, that the negative income elasticity pertains to a period of rising car ownership and use. As private motoring approaches saturation, which it must do eventually, or is limited by political means, it is likely that income's negative effect on bus patronage will become smaller, and possibly become positive.

Motoring costs are shown to have a significant positive influence on bus use, particularly in urban areas. Of the demographic variables included in the model — population density and the percentage of pensioners — only the latter is found to have a significant influence on bus patronage. The non-significance of population density is most probably explained by the fact that differences in population density between counties are captured by the county-specific fixed effects.

It is our general assessment that the average fare elasticities obtained and the relationship between short- and long-term effects are quite robust results, adequately supported by the quality of the data available and the statistical tests. The results for the individual counties are less well supported, and at least some of the differences noted are likely to be due to inadequate data, rather than reflecting genuine differences.

The values for the fare, income, and service elasticity variables obtained from the dynamic models in this study are broadly in line with those cited in the literature. The review in Dargay and Hanly (1999), which is based on those in Goodwin (1992) and Oum, Walters and Yong (1992), as well as more recent studies, suggests a consensus value for the short-run elasticity on the order of -0.3. There is also a good deal of empirical evidence that the elasticity increases over time, with the long-run elasticities generally from 1.5 to over 3 times higher than the short-run elasticities. Although there is far less agreement as to the long-run elasticity, the majority of estimates range from -0.5 to -1.0. A most striking feature of the reviews is the variation in the elasticities obtained in the individual studies, which is not surprising given the differences in data and methodology used and circumstances considered. The studies indicate that the fare elasticity varies by trip purpose, time of day and type of patron. The

[11] Romilly (2001) finds the income elasticity based on aggregate data for Great Britain to be positive. This appears to be due to the inclusion of a time trend amongst the explanatory variables, rather than to differences in model specification or methodology. Compare Dargay and Hanly (2002) using a cointegration approach on aggregate data. Introducing a time trend into the models estimated here shows that the time trend has a significant negative effect and changes the income elasticity from negative to positive. We do not include a time trend here, because it has no economic justification.

elasticity for leisure and other off-peak trips is about twice that for commuting, peak-time trips. Higher income groups seem to be more sensitive to changes in bus fares, and non-concessionary patrons more responsive than concessionary patrons.

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