Chapter 13

Forecasting the demand for transport

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Learning Outcomes:

On reading this chapter, you will learn about:

- Alternative approaches to generating a forecast of demand for existing, new or improved services
- Issues surrounding asking people how they or the public would react to new or improved transport services and the problems that will occur
- Methods for identifying trends and projecting demand for existing services when no major changes are expected
- Methods for identifying and projecting seasonal change
- Methods for forecasting demand when significant change is expected in the economic and social environment
- Methods for forecasting the impact of new or improved services in a competitive environment.

INTRODUCTION

In order to assess if the provision of a new or improved transport service makes economic sense we need to have some idea of how the public will respond, both immediately and, because transport investment has a very long life, in the far distant future. In Chapter 3 the theory underlying the demand for transport services was discussed. In Chapter 14 you will learn how we take our demand forecasts and assess if they represent a good use of our money. In this chapter we examine the practical issue of generating a forecast.

It should be emphasised from the outset that forecasting is not about applying a mathematical formula to a set of data but rather it is about collecting information from all relevant sources and analysing it in a consistent structured fashion. Remembering that transport is a derived demand, it is only when nothing significant is happening or expected in the external environment that the estimation of a mathematical trend or a pure data relationship is sensible. Thus, for example, when climate change and oil prices are having an impact throughout the world, projecting demand for air transport based only on air traffic data from 1970 to 2000 is not sensible. Huge and environmentally damaging investment in airports based on such trends would appear to be equally debatable.

Integrating information and data about the external environment mathematically can be extremely complex and, indeed, may be impossible. In some cases a set of human brains will produce better forecasts. However, the information in the brain has to be structured and organised or we can be guaranteed biased and inaccurate forecasts. Trend Analysis and unstructured groups vie with each other to produce the very worst outcomes. The cost of transport developments means that poor forecasts will generate significant reductions in the welfare of the public. However because of the regulated monopoly position of many/most transport suppliers, this will not be reflected in lower profits, only higher overall costs. Thus we, the general public, have a vested interest in ensuring that demand forecasting is taken seriously and the effort expended is proportionate to the costs to us all of getting it wrong.

Finally it should be noted that there has been extensive research on how best to forecast, much of which is, unfortunately, regularly ignored. Those wanting to carry out forecasting are recommended to consult *Principles of Forecasting: A Handbook for Forecasters and Practitioners* (ed: J. Scott Armstrong, 2001) which summarises much of the research and offers practical guidance. For the more general reader *Long-Range Forecasting: From Crystal Ball to Computer* by J. Scott Armstrong (1985) is strongly recommended for both entertainment and enlightenment.

GENERAL APPROACHES

There are, broadly speaking, three approaches to forecasting demand:

1 Qualitative: Surveys and Sampling
2 Time Series Analysis
3 Econometric Techniques.

Figure 13.1 provides a decision chart for this first choice of which method may be the most appropriate to use for a given situation.

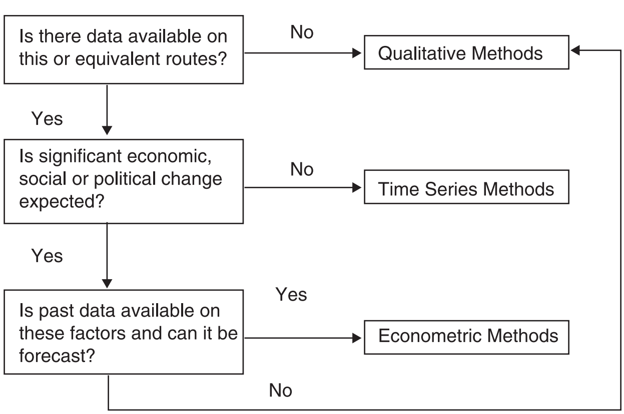

Figure 13.1 Choosing between methods

From this choice diagram there are some methods that will normally be associated with specific types of problems. Time series methods will normally only be relevant in the short term (when little externally will have changed). They are particularly strong at identifying and forecasting seasonal effects.

Econometric methods need a lot of good quality data that can only come from public sources. Some information will not be available for reasons of commercial confidentiality. There will also be some difficulty in forecasting some of the key factors, e.g. the price of oil in 25 years' time. Often we need to develop a range of possible futures for these determining factors (termed scenarios) and generate a separate forecast for each scenario.

Where there is no equivalent to the proposal, e.g. demand for travel to the moon, and no past data, then the intentions of potential customers or the opinions of a range of experts have to be sought. Intention Surveys will, in general, only be appropriate in the very short term. Expert opinions will be required for new products and the very long term that involves significant technological development. We now look at these Qualitative Methods and their potential problems.

QUALITATIVE METHODS

Qualitative Forecasting Methods are based on surveys of either potential customers or 'experts', such as key suppliers. Intentions information can provide the basis of excellent forecasts. As an example forward orders and commitments, such as deposits on holidays or numbers already booked on a service, provide an excellent basis for making forecasts up to one year ahead. Similarly asking existing customers of their intention to repeat the experience can provide excellent results.

The major problem with intentions is identifying who to ask. In some cases the target group may be relatively small and contained. A new bus route to a commercial estate for example will predominantly attract those who work or visit the estate and this group will define what is known as the sample frame. For an accurate representation of what people say we only need ask some of the group, what is known as a *representative sample*. It is important to ensure that no groups are over-sampled and none under-sampled, so it is necessary to ensure that questioning take place throughout the area and throughout the day. If we know the numbers in the various groups that make up the sample frame, e.g. the percentage of females over 60, then we can ensure that each group is properly weighted. Note that the numbers in each stratum do not have to be in proportion (although it can make calculations easier if they are) but there does have to be a significant number in the group sampled.

With new facilities and services, in the short term estimates tend to be too high. This is primarily because people over-estimate their capacity to change and always believe extending their options beneficial. A new bus service or cycle track may seem a wonderful idea when it is suggested but when the car is standing in the drive and the rain is pouring down, a commitment to use the bus or cycle to work will often be ignored. In the long term estimates may be too low because the population itself changes. Individuals without cars will find the estate more attractive as a place to work or shop and workers on the estate will choose accommodation along the bus route. Forecasts from intentions thus need to be adjusted up or down to account for known biases.

In some cases the population concerned is almost impossible to identify or is simply too large to sample properly. For example suppose we are interested in forecasting the number of people who might want to use a weekly service from a local airport to an airport in southern Italy. Potentially anyone in either local area, which will inevitably run into millions, might use the service and will need to be sampled. Suppose the number in both catchment areas is 6 million and we need over 6,000 customers (0.1 per cent) to make the service viable. Even if in fact 9,000 are interested we need a sample of 2,500 people to confirm that we exceed 6,000. If the actual is 20 per cent over the minimum the sample size needed is 12,000. This sampling has to be undertaken in both Italy and the UK adding further to the cost. Given the potential biases already identified and the relatively small cost of short-term transfers of buses, planes and even ferry boats, most firms prefer to simply try out possible routes for a limited period particularly if they can obtain local financial support from the origin and destination areas and they have some indication from 'gravity' models (outlined later in the chapter) that they might be viable.

Forecasting by opinions happens in every organisation at least once a year in the development of budgets. Politically every manager seeks to maximise the income to their divisions without exposing them to unrealistic sales targets. The sales targets will normally be based on the opinions of those 'on the ground' on the likely demand, particularly relative to existing demand. In practice the political imperative of meeting targets leads to diversion of marketing effort often involving price reductions. The outstanding record of low-cost airlines in flying close to capacity is not an indication of excellent forecasting by managers but of a pricing system that combines bookings data and pricing to ensure the plane is filled.

Forecasting using only expert opinion should normally be restricted to novel situations where the alternatives of asking potential customers or using a quantitative model based on similar situations are not available. Even then it is essential that experts from outside transport are involved, indeed it has been said that the only expert that should be used is an expert in forecasting. There are three major problems in seeking expert opinions, anchoring bias, group think and status deferral. Because 'experts' tend to be elderly they give weight to early experiences which may not be appropriate in times of rapid change. Thus anchoring bias often results in underestimates of the rate of change possible. Group think tends to have the opposite effect. In a group, individuals do not have responsibility for the outcome and are tempted towards more risky projects and higher forecasts than warranted. This is particularly apparent if the senior manager in the group is 'entrepreneurial' and a risk taker. In these circumstances ambitious individuals will invariably defer to the higher status individual since opposing, even if perfectly correct, tends to have negative career effects.

To overcome these problems four rules should be adhered to:

1 The group should be facilitated (chaired) by an external
2 Experts from a variety of disciplines should be used
3 All opinions should be given equal weight
4 Reviews of previous forecasts should always be undertaken.

One popular approach known as the Delphi technique (named from the ancient Greek forecaster The Oracle of Delphi) involves a group of individuals from different disciplines (and locations) who are physically separated. The experts individually present their forecasts and the arguments for them to all the others. They then revise their forecasts in the light of the forecasts of others and present them again. This carries out round after round until consensus is reached. The job of the facilitator is to identify, for the participants, the major points of dispute and, if necessary, force agreement on these as a pre-requisite to agreement on the forecast. In the early years the individuals were in separate rooms at the same site but current information technology provides a perfect platform for the technique.

Although expert opinion has a limited role as the sole forecasting method it is important in reviewing and modifying forecasts from the data-based approaches that are now discussed. It should again be emphasised that forecasting is about combining information from all sources in a structured fashion; experts will have knowledge that is not contained within the data.

TIME SERIES ANALYSIS

Introduction

On occasions we want to forecast demand for a transport service that has a long recorded history. Riddington (1999) for example was interested in forecasting the numbers using charter flights to skiing resorts in Europe, data which has been recorded by the Civil Aviation Authority since 1981. The Department for Transport records and forecasts the numbers using the various modes, road, rail, air and sea. Over time certain patterns emerge. The most obvious and important is fluctuations over the seasons.

A further example would be on short sea crossings, where we may expect higher demand in the summer than during the winter. Figure 13.2 shows the total number of passengers travelling on ferries to and from the UK each year and Figure 13.3 shows the number each quarter.

As expected, there is a marked seasonal pattern with passenger numbers rising steeply in the second and third quarters. There is also however a clear downward trend.

In time series analysis, from such cyclical patterns we seek to identify the three elements:

1 The Trend
2 Seasonal or Cyclical factors
3 The unusual (sometimes termed the stochastic factor or noise).

We then assume that these will continue into the future. As discussed earlier this may be reasonable, particularly in the short term. However, in this example, given changes in air fares, holdups

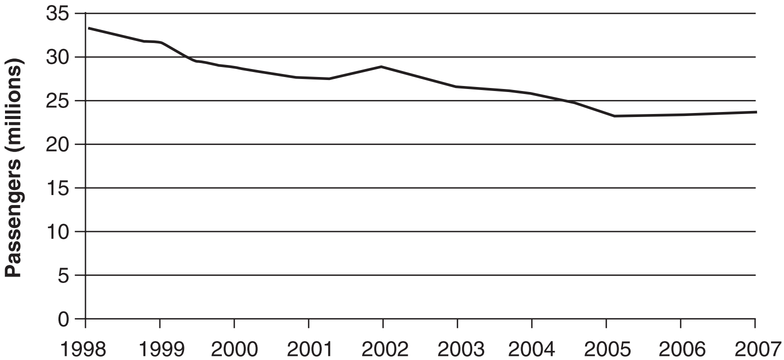

Figure 13.2 Annual and quarterly short sea passengers, inward and outwards, 1998 to Q2 2008

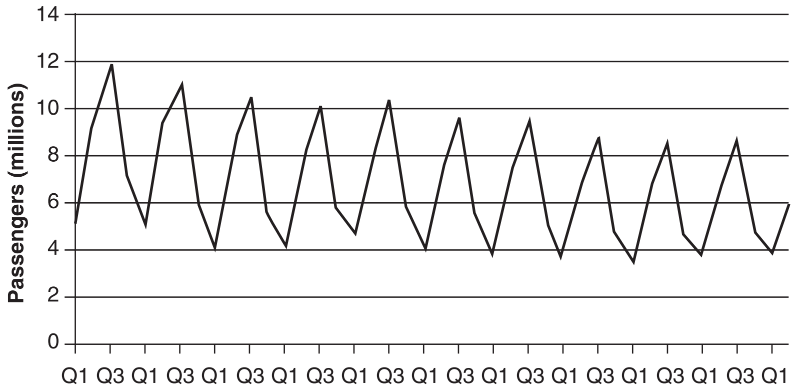

Figure 13.3 *Annual and quarterly short sea passengers, inward and outwards, 1998 to Q2 2008*

and delays at airports and faster ferries, it would be a very brave forecaster who would assume the downward trend illustrated will continue. A very well-known verse attributed to the famous economist Roy Harrod runs:

A trend is a trend is a trend,
the question is will it bend?
Will it change course
through some unforeseen force
and come to a premature end?

If the forecaster is interested in forecasting on a daily or weekly basis then a number of sophisticated methods such as ARIMA, ARARMA, Trigg-Leach and Brown's Double Smoothing have been developed. These involve weighted moving averages of the data to obtain an estimate of the underlying level and weighted moving averages of variations from that level. After a number of competitions between them, which method is 'the best' is still subject to much debate. Interested readers are referred to Makridakis and Hibon (2000) for further information.

Trend curve analysis

Most transport economists are primarily concerned with the medium to long term and one advocated approach is trend curve analysis. This approach involves trying to fit a line as closely as possible to the annual (or deseasonalised) series. The procedure of 'fitting' is known as Regression. Those unfamiliar with regression are referred to any introductory book on statistics or web sources such as Wikipedia, which gives a reasonable introductory overview. In essence regression replaces fitting lines by eye with fitting a line that minimises the square of the distance from the line to the point. Figure 13.4 shows the line of best straight line fit associated with the annual sea passenger series.

The formula for a straight line is $Y = \alpha + \beta X$ and the distance between the line and the actual number is known as the stochastic term, the error or the residual term and is symbolised by ε. Thus the formula for the actual number is $Y = \alpha + \beta X + \varepsilon$, where, in this case, Y is the sea

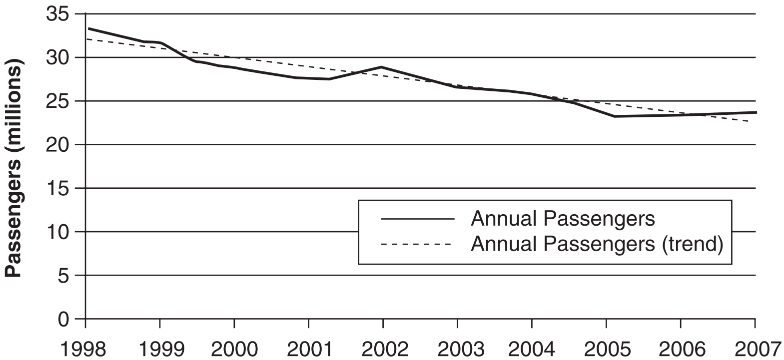

Figure 13.4 *Annual sea passengers, underlying trend*

Table 13.1 *Sea passengers per year*

Y (PAX)	*X (YEAR)*
33225861	1998
31381282	1999
28516814	2000
27753461	2001
28726426	2002
26523377	2003
25798730	2004
23693468	2005
23465161	2006
23667651	2007

Source: DfT Statistics

passengers and X is the year. To obtain values for α, β and ε we employ statistical software such as the Data Analysis Add-In in Excel. Table 13.1 shows the data and Figure 13.5 the output that is generated.

The coefficients give the values of α (2134399282) and β (−1052246.72). To obtain a forecast of passengers in 2020 we simply substitute 2020 for X in the formula $Y = \alpha + \beta X$, which gives 2134399282 − 1052246.72*2020 = 8,860,905. This is considerably (and implausibly) lower than the current level of 23,667,651.

The straight line implies that a fixed number of passengers (1,052,247) will be lost every year. In reality growth and decline is normally a fixed percentage rather than a fixed quantity. This is represented by an exponential curve $Y = \alpha * e^{\beta X}$ rather than a straight line. The exponential term e is rather like π in geometry, and has a fixed value of 2.718282. It is important because the equation results in a fixed growth rate given by β. Depending upon assumptions made about the stochastic term, the values of α and β can be estimated either by linear regression of $\log_e(Y)$ against X or by iteration. In this case the growth rate was found to be −3.8 per cent and the 2020 forecast 13,871,777 considerably higher than the linear forecast.

The question arises which forecast is ‘better’. Remembering that forecasting is about

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.9593
R Square	0.9203
Adjusted R Square	0.9104
Standard Error	994080.8077
Observations	10

ANOVA

	df	SS	MS	F	Significance F
Regression	1	91345910889887	91345910889887	92.43698	0.0000
Residual	8	7905573217590	988196652199		
Total	9	99251484107477			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	2134399282	219163227	9.7389	0.0000	1629007975	2.64E+09	1.63E+09	2.64E+09
X (YEAR)	-1052247	109445	-9.6144	0.0000	-1304626.64	-799867	-1304627	-799867

RESIDUAL OUTPUT

Observation	Predicted Y (PAX)	Residuals
1	32010333.35	1215528
2	30958086.62	423195.4
3	29905839.9	-1389026
4	28853593.18	-1100132
5	27801346.46	925079.5
6	26749099.74	-225723
7	25696853.02	101877
8	24644606.3	-951138
9	23592359.58	-127199
10	22540112.85	1127538

Figure 13.5 *Excel regression output*

combining knowledge then if there are strong reasons to assume fixed growth (bending trends) and/or that the results are more plausible, then that is the appropriate forecast. However, there are also some indications from the statistics that the ‘fit’ of the growth rate model is better. A measure of the fit is known as the Adjusted RSquared which for the linear is shown (on the third line of the output table) as 0.910391568. This suggests that we can explain 91 per cent of the variation in the data series by the model with 9 per cent being due to the stochastic noise, i.e. remains unexplained by the model. The adjusted RSquared for the growth rate model is 0.92326468, i.e. the exponential model explains more. It should be emphasised however that a good fit is not the same as a good forecast. Great care should be taken when selecting models using fit statistics because they are dependent upon a number of assumptions about the stochastic term that may well not be true. It should also be noted that, in theory, test statistics from linearised models are not directly comparable with those from simple linear models. That said it is a helpful additional factor in deciding whether a linear or exponential model is better.

Because fit and forecast performance can be radically different, if the data set is long enough, it is good practice to exclude the last few data points when estimating the model. Forecasts from the estimated model are then compared with the actuals (technically known as *ex post* analysis). There is some debate in the relevant literature as to the appropriate measure of the forecast. The most common is the Root Mean Square Error of the one step ahead forecast.

Estimating seasonal fluctuation by seasonal dummies

When planning capacity, if there is marked seasonal fluctuation, then a seasonal forecast is required. Again there are a large number of methods involving weighted averages of the seasonal differences (or ratios) some of which are quite complex. A simple approach utilising regression involves the use of dummy variables. A dummy variable is a variable that takes a value of 1 when the phenomenon is present and zero otherwise. It was originally developed to take account of periods of war in economic models but is equally applicable to the season. In the seasonal case a dummy variable for Q1 has a value of 1 when it is Q1 and zero otherwise. We can thus extend our example in order to incorporate not only the effect of time (the trend) but also seasonal effects into our forecasts. Table 13.2. shows the first two and a half years of the data set up in Excel and Figure 13.6 the results of the linear multiple regression of sales against the year and the seasonal dummies.

It is important to note that when you have four quarterly dummies you cannot also have a constant, as effectively the quarterly dummies are the constants for each season. The coefficient of X indicates the decline per quarter and the coefficients of the dummies are equivalent to the constant term for that quarter. Figure 13.7 shows how closely the model fits the data; some 97 per cent of the variation is explained.

To forecast we take the coefficient of the relevant quarter and add the coefficient of X * the time (i.e. 2020.25 for the second quarter in 2020).

The linear model estimated above implies a constant addition/subtraction to the mean for each quarter. However, most of the time, the seasonal effect is most likely to be a proportion of the underlying mean. As with the growth model a ratio seasonal factor can be estimated by regressing the log of the sales on to the time and the dummies. In fact this log-linear regression produced a remarkable fit and an adjusted R Squared just slightly higher of 97.3 per cent compared to 96.9 per cent for the linear model. Incorporating seasonal effects into our model therefore has improved the overall fit, and hence may be expected to produce better forecasts.

Table 13.2 Quarterly sea passengers with seasonal dummies – first two and a half years

Y (PAX)	X (YEAR)	Q1	Q2	Q3	Q4	LogY
5151807	1998.00	1	0	0	0	15.45486
9304349	1998.25	0	1	0	0	16.04599
11801764	1998.50	0	0	1	0	16.28376
6967941	1998.75	0	0	0	1	15.75683
5036822	1999.00	1	0	0	0	15.43229
9452280	1999.25	0	1	0	0	16.06177
10996127	1999.50	0	0	1	0	16.21305
5896053	1999.75	0	0	0	1	15.58979
4179625	2000.00	1	0	0	0	15.24573
8464104	2000.25	0	1	0	0	15.95134
..	..	..	..	..	..	..
..	..	..	..	..	..	..
..	..	..	..	..	..	..
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SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.9985
R Square	0.9970
Adjusted R Square	0.9696
Standard Error	416052.4587
Observations	42

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	5	2.12E+15	4.24E+14	2447.337	0.0000
Residual	37	6.4E+12	1.73E+11		
Total	42	2.12E+15			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
X (YEAR)	-252670	21204	-11.9162	0.0000	-295633	-209707	-295633	-209707
Q1	510286258	42471791	12.0147	0.0000	424230237	5.96E+08	4.24E+08	5.96E+08
Q2	513756509	42477092	12.0949	0.0000	427689746	6E+08	4.28E+08	6E+08
Q3	515932721	42471809	12.1477	0.0000	429876662	6.02E+08	4.3E+08	6.02E+08
Q4	511627864	42477110	12.0448	0.0000	425561064	5.98E+08	4.26E+08	5.98E+08

Figure 13.6 *Output from regression of sea passengers on time and seasonal dummies*

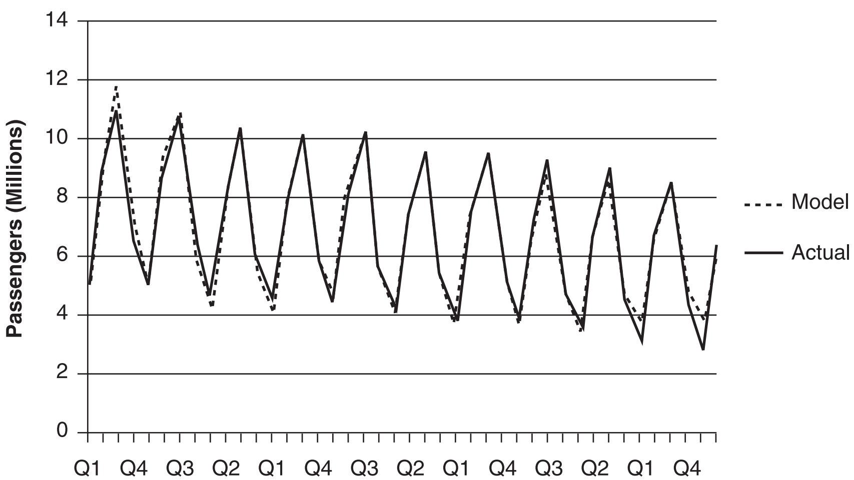

Figure 13.7 *Actual and estimated sea passengers by quarter*

Unlike the trend, the factors that determine different levels throughout a season do not change; Christmas always occurs on December 25th, the summer holidays in July and August etc. Problems do occur when dealing with monthly data due to situations when there are 5 weekends or when Easter occurs in March rather than April but, certainly at quarterly level, estimates of seasonality are accurate and robust. This is, however, not the case with trends. Whatever has caused the decline in sea passengers may quite conceivably reverse or become more important. Investigating what has determined change and using that information to forecast the future is the role of econometrics, which we cover next.

ECONOMETRIC METHODS

Introduction

In Chapter 3 we looked at the factors that broadly determine the demand for transport; income, price, quality of service, price and quality of alternatives, journey time and population size. The object of econometric methods is to try and identify the precise importance of each of these (the usual measure being the elasticity) in order that we can determine the effect on demand of changing these in the future. Unfortunately, as we shall see, this is not necessarily a straightforward task.

The modelling process involves 6 stages

1 *Understanding the Problem*: Identifying all the key factors and making preliminary estimates of the size and direction of the effect. This is covered in Chapter 2.
2 *Obtaining the Data*: Data on ALL the factors has to be acquired. It is no use having price data for your company but not for your competitors. Data is of three broad types:

    a) Time Series, where the data, going back a significant number of years, relates to a single location
    b) Cross Section, where the data has been obtained from a series of locations (or individuals) at a specific point in time
    c) Panel Data, where data has been obtained from the same series of locations over a period of years.

    Each type of data has strengths and problems specific to it which we will discuss in the next sections but, generally speaking, the major problem is acquiring good quality data at all. Statistics issued by the government or its agencies are invariably the first place to look, e.g. Transport Statistics, National Statistics, The Census and the National Travel Survey. The Civil Aviation Authority also produces some superb data series. All these are now available on the Web.

    It is extremely difficult however to obtain good data on two key factors, Price and Quality. Consider trying to ascertain the impact of a more expensive but faster train from Scotland to England. This needs information on the changing quality of the experience, journey times, frequencies, changes in airport check-in time, queues at security, over-crowding, traffic jams etc.

    Equally critical is the actual price paid both on the train and the competitive air, coach and road services. Because the average price paid is a commercial secret we are forced back to published ‘normal’ prices which may be substantially higher than actual price. In addition, in the case of some airlines, the published price varies from hour to hour depending upon the current loading. The ‘cost’ in both journey time and ticket price, of getting to the final destination, must also be acquired.

A fundamental problem is that the omission of a key variable totally distorts estimation of the impact of the other factors. Poor or substitute (proxy) data is better than no data but inevitably decreases confidence in the outcomes.

3 *Specifying the Model:* It is tempting to assume that the factors are independent of each other, that the factors are additive in their effects and the effect happens immediately and that all the assumptions relating to the stochastic term are applicable. Unfortunately that is rarely the case. The specification stage involves:

a) Selecting the functional form (linear, log-log, logistic etc)
b) Selecting the variables and in time series any lagged effects (e.g. with advertising)
c) Making reasonable assumptions about the stochastic term (e.g. that the bigger the demand the bigger the stochastic term).

4 *Estimating the specified model*: Identifying values for the parameter estimates for each factor to be used in the forecast α, $\beta 1$, $\beta 2$, $\beta 3$, . . . that makes the predicted values lie as close as possible to the actual values. This normally involves minimising the sum of squares of the residuals.

5 *Validating the Model*: This involves examining the outcomes to ensure:

a) The values of the coefficients (the elasticities) have the right signs (income positive, price negative and so on) and are of the expected size
b) The fit is statistically significant (The RSquared and F values in the output table)
c) The individual variables are statistically significant (the t value in the output table)
d) The residuals have no pattern over time or location.

If the model fails these tests then we need to return to the specification stage (or even the understanding).

6 *Simulation/Forecasting:* Once we have the final model then it is a question of inserting expected future values of the factors into the equations. Sometimes we can use forecasts from other organisations but often we need to use suggested values obtained from expert groups. Sometimes different sets of predictions are bundled up to form scenarios. Sometimes we simply use trend extrapolation of the external factors.

This last section illustrates a theme of this chapter. The purpose of econometric modelling is both to obtain information on the effects of the demand factors but also to integrate information from a variety of sources into the forecast. We now look at some important specifications and problems associated with them before illustrating how these come together in assessing demand for a new route.

The gravity model

It would be extremely surprising if the demand for services (which includes the demand for road space for cars and lorries) between two large cities such as London and Manchester was not much, much larger than between two small towns such as Cirencester and Lincoln. It would also be very surprising if the numbers travelling between two adjacent towns say Cambridge and Norwich was not much larger than between Cambridge and a town of a similar size to Norwich in Scotland, say Dundee. Hence the level of transport between two locations will be dependent upon their respective population sizes and the distance between them. In more formal terms, our understanding suggests that the flow of people between two points i and j, F_{ij}, is a function of the size of the origin O_i, the size of the destination D_j and the cost of travelling between them C_{ij}. At this stage it is important to note that the cost is directly related to the distance between i and j and the time taken; a direct motorway will reduce the time and hence decrease what we term the generalised cost.

To estimate our model in order to predict the numbers flowing down a particular route we need data on flows between a number of towns and the generalised cost of travelling a route. This is a typical example of cross sectional data.

The normal specification of the model is of the form:

$$F_{ij} = \alpha O_i^{\beta} D_j^{\gamma} C_{ij}^{\delta} \varepsilon_{ij}$$

where α, β, γ and δ are parameters to be estimated and ε is the stochastic term. In simple terms, what these show is the relative impact each factor will have on the numbers travelling between these two locations taking into account the differing units these may be measured in. Thus for example the β is the impact of the size of the origin on total traffic flow. In a similar fashion, γ is the impact of the size of the destination and so on. The gravity model gets its name from the models of gravitational pull developed by Newton where the size of the bodies is multiplied together with the distance between them.

It is also very easy to estimate the model by taking logs to give:

$$\log F_{ij} = \mathrm{A} + \beta \log O_i + \gamma \log D_j + \delta \log C_{ij} + \mathrm{E}_{ij}$$

where A is log α and E is log ε. If we assume that E is normally distributed then the normal method of minimising the sum of the squares of the stochastic term (known as Ordinary Least Squares) can be applied.

Riddington (2002) used a gravity specification to forecast the numbers of people who might travel to a new supermarket in town H. The numbers of people in each of the 12 surrounding towns and villages was known. The complication was the existence of 3 other supermarkets in town D which currently attracted custom from the same towns and villages. The two key determinants of the proportion of each settlement that would go to H rather than D was the relative distance to H and the relative size of the shops; the more floor space/goods on offer, the more attractive the destination. It was assumed that a fixed proportion of each settlement would shop in either H or D in any week. A possible range of values for the impact of supermarket size and distance were obtained from other gravity model studies. The mean of these values generated a central forecast, the range of values and the possible range of outcomes. This work showed conclusively that the estimates of diversion from D to H made by the proposers was exaggerated and that, even at the most favourable range of values, the new supermarket would lead to serious problems and small shop closures in the existing town centre.

The gravity model is central to large network planning transport models, particularly the four stage Transport Planning Model, where stage one and two are to estimate the total number of trips within a given area, and then the number of specific flows between two locations, before subsequent stages then apportion these flows to modes and then routes. Gravity models are also extensively applied in models of economic trade and thus used to predict trade flows. Nevertheless, the focus is on populations and generalised costs and the specification is totally unable to describe the massive growth in car and air journeys. For this we turn to traditional demand models formulated over time.

Econometric demand models

Whilst population change is of critical concern in a local context and in developing countries, in the developed world it has been relatively static and is not an explanation for the growth in transport that has been a characteristic of the last century. As seen in Chapter 2, we have tended to associate this growth with the growth of the economy and the associated growth in real personal incomes.

Our understanding based on the theory of Chapter 3 suggests that, at the national/regional level, the demand for a particular mode (road, rail, air, sea) will be determined by National Income, comparative price, comparative journey times, frequency and comparative quality. Data for income over a number of years can be obtained easily. Journey time information for the same years needs to be identified with allowances for travel to public transport and times to enter and exit the terminal (including the time to wait for the service). As discussed earlier, obtaining good quality price data for a number of years is problematic and normally ad hoc series based on what can be obtained over the years has to suffice. Finally there is the issue of comfort. The modern car is significantly more comfortable and reliable than its real price (i.e. net of inflation) equivalent of twenty years ago whilst the low-cost airline is not as luxurious as its historical forebears. We normally either:

1. Simply assume quality changes are part of the stochastic term (not normally appropriate)
2. Allow for these changes by introducing proxy variables that are linked to quality
3. Develop what are known as hedonic price indices.

Broadly speaking econometric demand models have two functional specifications: linear and multiplicative (log-log). There is some evidence that consumer responses to economic changes are constant, e.g. that a 10 per cent rise in incomes will lead to a 7 per cent increase in demand, whatever the current level of income. This is a situation of constant elasticity and is characteristic only of a multiplicative model. Thus, on these grounds alone (there are others), the following specification might be used:

$$Log\ Q_t = \alpha + \beta_1 \log Y_t + \beta_2\ Log\ P_t + \beta_3\ Log\ J_t + \beta_4\ Log\ F_t + \varepsilon_t$$

Where Q_t is number of passengers, Y_t is income, P_t is relative price, J_t relative journey time and F_t is relative frequency. Once again in simple terms the parameter estimates (β terms) are the relative impacts on demand of each of the factors included, taking into account the units in which each is measured.

Because of the difficulty with national data on Price, Journey time and Frequency, a truncated form $Log\ Q_t = \alpha + \beta_1 \log Y_t + \varepsilon_t$ is often found (e.g. DfT traffic forecasts). The relationship between demand and income is very strong and found throughout the developed world. It is also very easy to make forecasts. For example if β_1 (the income elasticity) in a model of car journeys has a value of 1.4 then growth in GDP of 2 per cent will lead to a growth of 2.8 per cent in car journeys. Of course forecasts of GDP for 20 years ahead are required in order to forecast transport demand 20 years ahead. In practice we normally present a range of possible growth rates for the economy and consequently a range of possible forecasts.

It is undoubtedly true that this procedure simply replaces a trend curve projection for passengers with a trend curve projection for the economy as a whole. However, other information about economic factors may be available and one of the most important strengths of this approach is the structured combination of information about the future. Unlike the time series approach outlined earlier, we are not only reliant on a single past trend within the transport system, but also the impacts of external factors upon that trend. Hence if a trend was to bend, there would be a far higher possibility that our forecast will pick it up.

The use of only GDP in the specification rather than all the variables is much more critical (as is the omission of lagged values in short period models). Suppose that over the same period the relative price of motoring has been falling. If it had a price elasticity of −1 and prices fell at 1.5 per cent per annum then the growth rate due to price change is 1.5 per cent. If the total growth is 2.8 per cent then only 1.3 per cent of that growth is attributable to economic income, not the full 2.8 per cent. If the decline in relative price was reversed then growth due to price change would be negative and the growth rate correspondingly lower. Thus it is absolutely essential that we include all relevant variables or the results concerning individual elasticities can be totally misleading. Failure to include the correct variables or the correct functional form is known as misspecification.

Misspecification and the demand for ferry services

Earlier in this chapter we observed the number of ferry passengers in decline. Since foreign travel is a luxury, our economics suggests it is likely to grow with income, hence it will have a positive price elasticity. We might also suspect that cheaper more available air services and the advent of the Channel Tunnel might have an effect on demand for ferries. Table 13.3 shows data collected on passenger numbers by different modes from the Social Trends database.

Our first task is to see how well our basic understanding fits to the data. Graphing the data is always a good start but in this case Figure 13.8 does not tell us much that we did not already know.

Another useful tool is the correlation matrix. This shows how closely any two series are aligned. A figure close to +1 shows a strong positive (complementary) relationship, close to −1 a strong inverse (competitive) relationship. For example we would expect number of cars and sales of petrol to have a high (>0.8) correlation but number of cars and bus passenger numbers to have a strong negative correlation. (<–0.8). Tables 13.4 and 13.5 show the correlation matrices between the numbers by mode and real GDP for data from 1981 and from 1995.

A significant difference between the two is the strong negative correlation between Sea Travel and Income in recent years (–0.93). It may be that this reflects the idea that sea travel on holiday is

Table 13.3 UK international passengers by mode (million)

YEAR	AIR	SEA	TUNNEL	TOTAL	REAL GDP
1981	11.4	7.7	0.0	19.0	56.2
1991	20.4	10.4	0.0	30.8	73.0
1995	28.1	10.0	3.2	41.3	79.5
1996	27.9	10.7	3.5	42.1	81.7
1997	30.3	11.5	4.1	46.0	84.3
1998	34.3	10.5	6.1	50.9	87.1
1999	37.5	10.4	5.9	53.9	89.7
2000	41.4	9.6	5.8	56.8	93.1
2001	43.0	9.7	5.6	58.3	95.3
2002	44.0	10.0	5.3	59.4	97.3
2003	47.1	9.2	5.1	61.4	100.0
2004	50.4	9.0	4.8	64.2	103.3
2005	53.6	8.1	4.7	66.4	105.2
2006	56.5	8.4	4.7	69.5	108.2

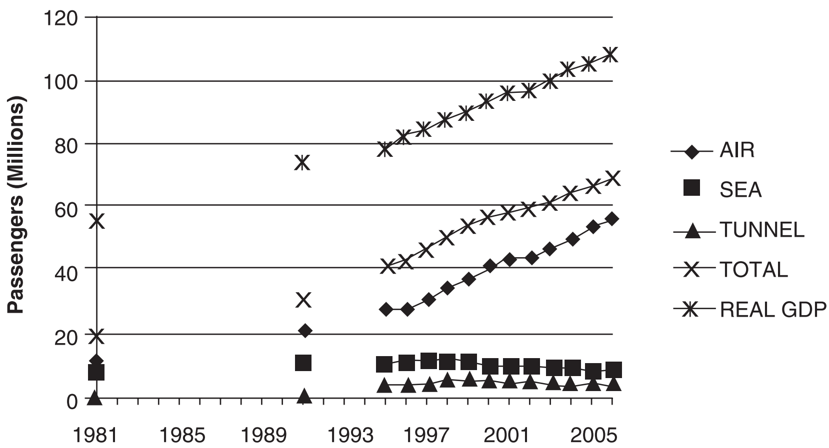

Figure 13.8 UK international passengers by mode

Table 13.4 Correlation matrix. Passengers by mode from 1981

	AIR	SEA	TUNNEL	TOTAL	REAL GDP
AIR	1.0000				
SEA	–0.2784	1.0000			
TUNNEL	0.7433	0.1755	1.0000		
TOTAL	0.9886	–0.1499	0.8270	1.0000	
REAL GDP	0.9900	–0.1485	0.7698	0.9933	1.0000

Table 13.5 *Correlation matrix. Passengers by mode from 1996*

	AIR	SEA	TUNNEL	TOTAL	REAL GDP
AIR	1.0000				
SEA	–0.9471	1.0000			
TUNNEL	0.1440	–0.0812	1.0000		
TOTAL	0.9939	–0.9226	0.2437	1.0000	
REAL GDP	0.9975	–0.9354	0.1044	0.9890	1.0000

an inferior product with a large negative income elasticity, i.e. as we get richer we are ceteris paribus less likely to take our cars on to a ferry to Europe. Conversely we may well believe that this is a short-term effect brought on by rapidly declining air fares in recent years and that the longer series with a very much weaker correlation (–0.148) is a better indication of what to expect in the future. It is important to recognise that our understanding from economic theory of what underlies change is crucial to modelling and forecasting.

To forecast demand for sea ferries we really require the price of ferry services, price of air services and the price of tunnel services. As discussed earlier obtaining a 'price' for a single route is extremely difficult, for a combination virtually impossible. Since we expect price and demand to be quite strongly inversely related we can sometimes use 'numbers' as proxies for prices. In addition the number of air passengers also reflects speculative increases in capacity. Thus it seems quite reasonable to try to explain the number of sea passengers by numbers on the other modes and income.

Figure 13.9 gives the Excel Output of the multiple regression of Number of Sea Passengers on passengers using air services, passengers using the tunnel and GDP.

The overall fit of the model is very good (95 per cent variance explained) but, more importantly, the model coefficients seem to have the right sign. The income elasticity of demand was defined in Chapter 2 as the rate of change in Quantity divided by the rate of change in Income, i.e in symbols $(\Delta Q/Q)/(\Delta Y/Y)$ or $(\Delta Q/\Delta Y)/(Q/Y)$. In a linear model $\Delta Q/\Delta Y$ is given by the slope of the line, i.e. the coefficient (in this case 0.429856). The elasticity will, however, vary over different values of Q and Y so, by convention, it is usually calculated at the mean values of Q and Y. The income elasticity of sea travel calculated at the means in this example is very high at just under 4. Surprisingly the truncated data gives almost identical results.

This modelling exercise is important because it highlights the way that increases in air passengers, rather than the channel tunnel, has been the most important factor in slowing down demand for ferry services. If airline growth is checked because of higher fuel prices and carbon pricing then we would confidently expect significant growth in the ferry market well in excess of the growth of GDP.

It is important to note that if data on prices were available it would be far better than using the proxy variables of passenger numbers. In addition a better modelling strategy, which is illuminated in the case study at the end of this chapter, might well be to model the total market and relate that to GDP and model mode choice separately based on factors such as price and journey time.

The use of ordinary least squares is in theory limited to situations where the stochastic term:

SUMMARY OUTPUT

Regression statisitics	
Multiple R	0.978422
R Square	0.957309
Adjusted R Square	0.944501
Standard Error	0.253175
Observations	14

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	14.37331	4.791102	74.74673	3.77E-07
Residual	10	0.640978	0.064098		
Total	13	15.01429			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	–10.5864	1.869482	–5.66274	0.000209	–14.7519	–6.42093
AIR	–0.51199	0.039174	–13.0696	1.3E-07	–0.59927	–0.4247
REAL GDP	0.429856	0.037769	11.38123	4.8E-07	0.345701	0.51401
TUNNEL	0.232451	0.05696	4.080982	0.002211	0.105537	0.359365

Figure 13.9 *Regression output from Excel*

1 Has Zero mean
2 Is normally distributed
3 Has constant variance
4 Is independent over time and space
5 Is uncorrelated with the independent variables.

As discussed earlier, there are also problems if the factors are not independent of each other. Econometric packages offer a number of estimation methods to deal with these problems and these are important if the main objective is to identify precisely the effect of one factor on another and the data quality is good. However, when we come to forecasting, low-quality data and the problem of obtaining good forecasts of the independents normally means the accuracy will always be limited. In these circumstances research suggests that theoretical sophistication is not as important as structured thought about the future.

MODELLING CHOICE

Background

It is often the case that we are more concerned with forecasting the share of existing traffic than the growth of that traffic. Consider, for example, investing in a new toll motorway that runs almost parallel to an overcrowded existing motorway. The key question is how many vehicles we might expect at various levels of toll. The first task is to generate a gravity type model that incorporates tolls and reduced journey times within the generalised cost function. This will then give us a first estimate at the total traffic on the route. The next task is to share the traffic between the toll and the free motorway. This is not however the end of the game because if the tolls are set too high, traffic will stick to the free motorway, journey times overall will increase and traffic will drop on both. In these type of situations we undertake what is known as *iteration*, i.e. we put the new forecast of traffic and journey time/average price into the model, generate a new share, recalculate total demands and generalised costs, re-estimate shares, re-estimate costs and totals, and so on. Modelling choices and shares is not, however, straightforward.

Based on our economic theory we assume that we will not undertake a journey unless we achieve some Utility (satisfaction). Against that we have to place the Cost, in terms of journey time (J), price (P) and lack of quality (L). We represent the importance of, for example, each minute or of an inch of leg-room by β_1 and β_2. We call the sum of the values generated from the factors the systematic value which for a choice Q is given by $V_q = \alpha - \beta_1 * J_q + \beta_2 * L_q - P_q + \varepsilon$.

Thus say service Q is chosen over service R, or service Q is chosen over service S, and so on, then we assume that it is likely that the systematic value of Q is greater than the systematic value of R, S, ... i.e. the difference between V_q and V_r, V_s, . . . is likely to be greater than 0 (or the ratio >1).

Data and specification

Choice modelling data comes in two forms:

1 Individual Data gathered within one time period
2 Market Share data which can be cross section, time series or panel.

Increasingly, when contemplating quality changes, a survey is undertaken where customers are presented with a number of alternatives and asked to choose between them. For example we might be interested in the best mix of speed, comfort and price on a train route. Customers are presented with a set of combinations of the three at different levels and asked to select their choice. They will then be presented with another set of combinations, and their choice recorded and then a third set and so on. This generates a mass of individual data and is known as a Choice Experiment.

For market share data Pr(Q) symbolises the proportion making a choice (e.g. going by mode Q). For individual data Pr(Q) symbolises the probability that the individual will make a choice (e.g. go by mode Q). Note that we cannot measure this probability, only the result. We assume that the choice with the highest chance of being selected will in practice be selected.

Assume for the moment there is only one alternative to mode Q, mode R. The larger the utility of mode Q relative to R, the higher the value of Pr(Q). It would be possible to simply regress Pr(Q) against the difference in the systematic values of Q and R, e.g. $Pr(Q) = \beta(V_q - V_r) + \varepsilon$. This is illustrated by the straight line SS in Figure 13.10

Note that when the utilities of R and Q are equal, the predicted market share (probability) must be 50 per cent. Note also that $Pr(R) = 1 - Pr(Q)$. Thus ever larger negative values of $Vq - Vr$

increase the probability that an individual will use mode R, whilst ever larger positive values increase the probability that an individual will use mode Q.

There are two major problems with this linear specification:

1 It suggests that it is possible to have more than 100 per cent of the market
2 It contradicts the law of diminishing marginal utility.

In this context the law simply tells us that, even if mode Q is vastly superior to mode R, a few people will still opt for R. Thus we would expect the line of best fit to look more like Figure 13.11

One mathematical function that gives a line of that shape is known as the Logistic and has the form

$$\Pr(Q) = \frac{e^{\beta(V_q - V_r)}}{1 + e^{\beta(V_q - V_r)}}$$

where e is the exponential operator (a constant).

With this function when:

$Vq = Vr$, $\Pr(Q) = 0.5$,
$Vq - Vr$ is very large, Pr(Q) tends to one,
$Vq - Vr$ is large and negative, Pr(Q) tends to zero.

At first sight this looks very difficult to deal with, but some simple algebra produces:

$$Log_e\left(\frac{\Pr(Q)}{1 - \Pr(Q)}\right) = \beta(V_q - V_r) + \varepsilon$$

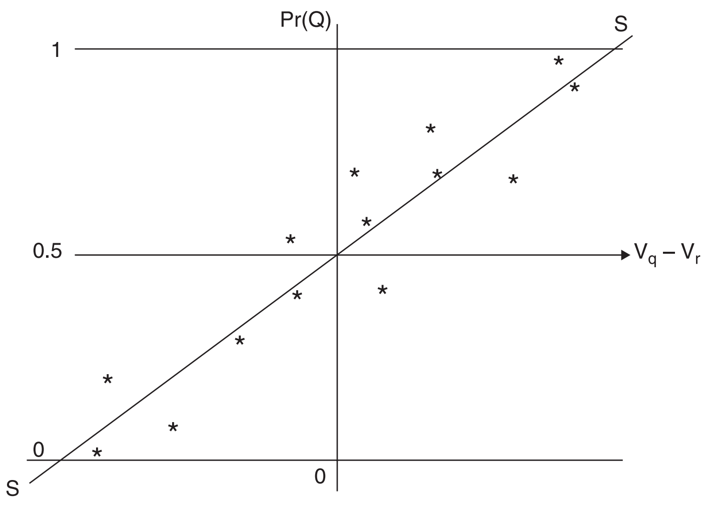

Figure 13.10 Change in market share versus difference in systematic values

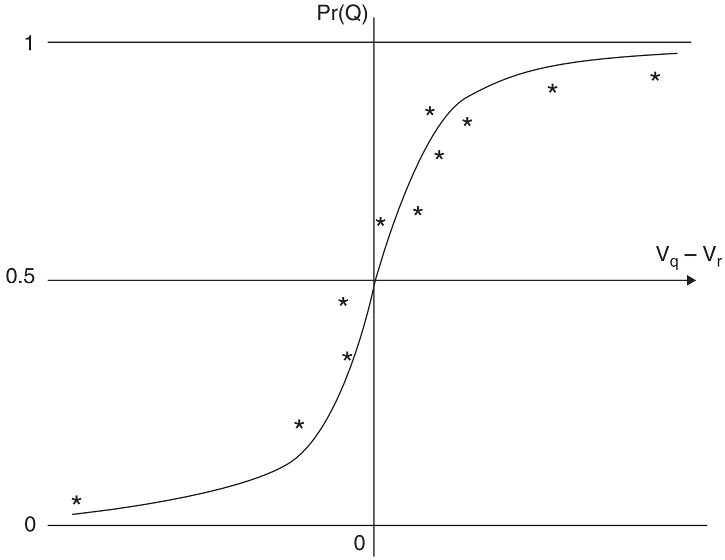

Figure 13.11 *The Logistic curve with market share data*

In order to clarify this 'simple' algebra, if we let $\beta(V_q - V_r) = x$ and $Pr(Q) = y$ then $y = e^x/(1 + e^x)$. Since $(1 + e^x)y = e^x$, $y = e_x(1 - y)$ and $y/(1 - y) = e^x$. Taking logs gives $Log_e(y/(1 - y)) = x$.

The first term is known as the LogOdds and is simple to calculate. For example if mode Q has 60 per cent of the market then R has 40 per cent and the logOdds is $log_e(0.6/0.4) = log_e(1.5) = 0.405$. To estimate β where we have proportions data, we simply carry out the normal regression of the LogOdds against the differences in the systematic values.

The problem with individual data is that we can only observe the choice made, i.e. it is either 100 per cent mode Q or 100 per cent mode R. This is illustrated in Figure 13.12.

Where the difference is very large we would expect the choice to be obvious. However, where our model predicts that for example there is a 53 per cent chance that the individual will choose Q then we will not be very surprised if they choose R. We use this idea to choose the parameters β to ensure that the situations when the predicted likelihood is high, then that is the appropriate choice and are less worried at values close to 0.5. This approach is known as Maximum Likelihood Estimation and is available in large statistical packages such as SPSS, LIMDEP or STATA. It is important to note that, because there is not much information conveyed by each individual about the 'norm', very large amounts of individual data (typically in excess of 1,000 individuals) are needed for reliable forecasts.

Forecasting shares

To summarise, the economic understanding suggests that choices are made on the basis of differences between factors such as journey time and price. Data can be either from individuals on their choices or from the market on the shares. The specified model has to take into account the logical limits of proportions and the law of diminishing marginal utility. One common form is the

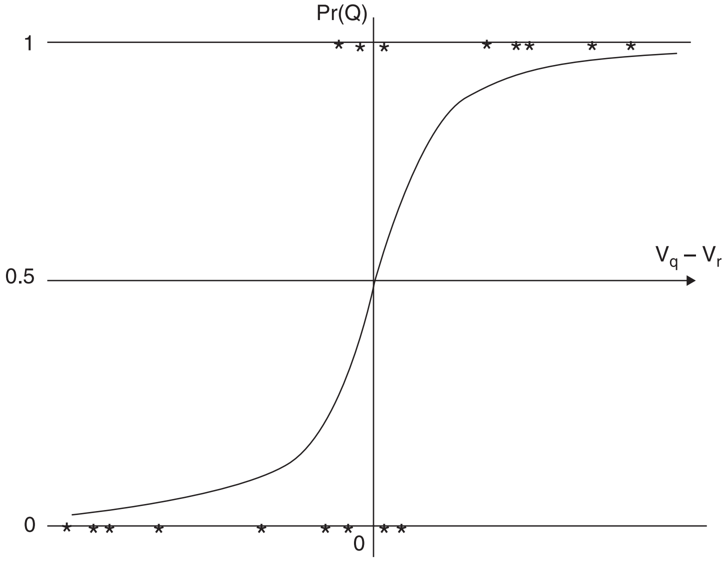

Figure 13.12 *Logistic curve and individual data*

Logistic although other forms such as the cumulative normal, known as the probit, can be used. Estimates of the parameter coefficients are found by regression of the LogOdds on the difference in the factor levels. In the case of proportions data we can use Ordinary Least Squares (OLS) regression (the usual approach) but for individual data we require specialist Maximum Likelihood techniques. Once we have the model estimated then forecasting is simply, as before, a case of substituting new values into the model.

Table 13.6 gives some of the data of mode shares between metropolitan areas (some of which are on islands).

This data generated a model of the form:

$\text{Log}_e(\text{Pr(Land)}/\text{Pr(Air)}) = -0.04 * (\text{Difference in Journey Times}) - 0.03 * (\text{Difference in Price})$

Table 13.6 *Sample data on market shares and differences in systematic values*

	Complete Journey Time (Mins)			*Price (£)*			*Share*	
Location	*Land*	*Air*	*Difference*	*Train*	*Air*	*Difference*	*Train*	*Air*
1	350	120	230	56	98	−42	0.0%	100.0%
2	280	280	0	98	98	0	50.0%	50.0%
3	35	120	−85	56	98	−42	99.1%	0.9%
4	90	80	10	88	78	10	33.2%	66.8%
5	620	134	486	25	231	−206	0.0%	100.0%
6	324	212	112	45	123	−78	10.5%	89.5%
7	350	220	130	56	98	−42	1.9%	98.1%

Or

Pr(Land) = exp(−0.04 *(Difference in Journey Times) − 0.03* (Difference in Price))/
(1 + exp(−0.04 *(Difference in Journey Times) − 0.03 *(Difference in Price))

Suppose current differences are 60 minutes faster by air and £100 more expensive but increased security increases air journey times by 50 mins. The model forecasts that the current land market share will increase from 64.6 per cent to 93.1 per cent.

Developments in choice modelling

The importance of the topic, coupled with major advances in computer power, have led to very significant and important developments in choice modelling. The most obvious has been extension to models with more than two choices. The simplest of these, the multinomial logistic, has a significant limitation (known as the independence of irrelevant alternatives) and a model that nests choices is often preferred. In the nested case a first choice might be public v private followed by a choice between bus and train after public has been chosen. Estimates can vary significantly depending upon the way the nests are constructed. Figure 13.13 shows two possible structures for a comparison of road, rail, car and coach. Once again our understanding of the way people make decisions is critical to the parameter estimates and ultimately the forecasts.

More recently developments in optimising algorithms have opened the possibility of multinomial probits with and without subjective priors (e.g. estimates of the degree of independence between the choices which are made by the modeller on the basis of their experience and understanding). It must be emphasised that these developments are dependent upon many thousands of observations of the choices made, and are most usefully found with choice experiment data. Readers that want to find out more are recommended to read Ben-Akiva and Lerman (1985).

Before concluding this chapter we look at a real case where most of the topics discussed come together.

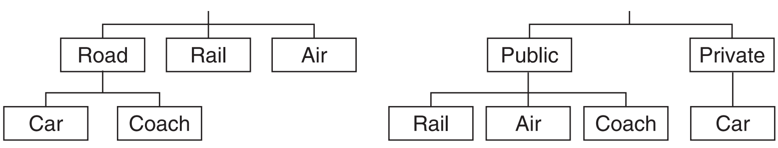

Figure 13.13 *Possible nesting structures for a four mode choice*

Case study 13.1 Forecasting demand for a new ferry service

– This case is based on Riddington (1996).

Background

Islay and Jura are two large adjacent island off the South West of Scotland. Although similar in size (253 and 147 sq miles respectively) they are remarkably different in character. Islay is relatively flat and fertile and sustains a substantial population of 6,500. Jura is a much wilder island with a backbone of mountains known as the Paps. Despite its closeness to the mainland the population is only 461, giving it one of the lowest population densities in the UK. There is only one minor road running up the lower two thirds of the island.

Transport to Islay is based around 3 return services per day from Kennacraig on the mainland to Port Askaig or Port Ellen on Islay, the crossing taking some 2 hours. A short ferry from Port Askaig provides the link to Jura.

On Wednesdays the basic service is modified with the morning boat continuing on via Colonsay to Oban and returning in the afternoon. This service aims to provide the possibility of a day shopping trip to the mainland but clearly demonstrates the relative isolation of the islands, 7 hours on some of the roughest water in Scotland for four hours ashore. Not surprisingly alternative routes and services have been suggested and this case is concerned with one of these, a short sea crossing to Jura.

As can be seen from the map (Figure 13.14) the crossing from Keills to Lagg is only 5.8 miles and would take just over 20 minutes. An hourly service is thus feasible with just one vessel. The vast majority of passengers would then proceed south through Jura to the second 15 minute crossing to Islay. Total journey time to Islay, using the short sea crossing, would be roughly halved.

In 1988 the government commissioned consultants to examine the economics of the proposed service. The consultants used *Trend Curve Analysis* to project demand overall and an *Intention Survey* of current customers to identify the proportion of passengers who would transfer to the new service. *Time Series Analysis* was used to identify seasonal fluctuation to identify the capacity that would be required.

This research forecast considerable demand for the new service. However, it was also clear that the road system both on the mainland and on Jura would need to be significantly improved at major cost. In addition it was claimed that the new link would be unsuitable for the heavy lorry traffic from the distilleries and a direct service from Islay would still be required. To the dismay of many local groups, the proposal was not continued because of the substantial road investment required.

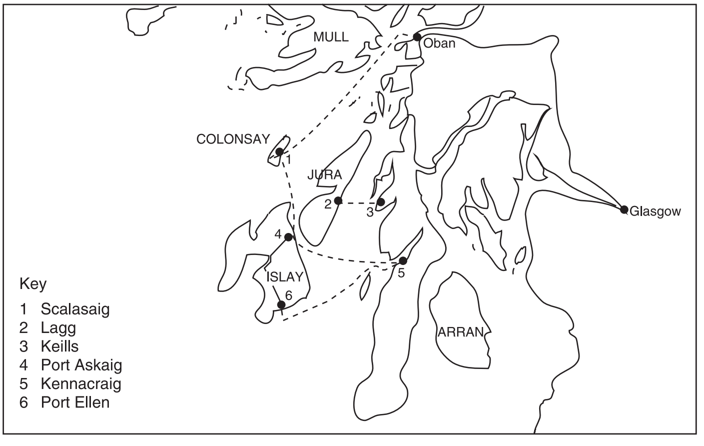

Figure 13.14 *The Islands of Argyll in South West Scotland*

The forecasts developed used by the consultants were the subject of some criticism and in 1996 were re-examined. In the 1996 case an *Econometric Demand* model was developed and then a *Choice Model* to identify likely market shares.

The model of overall demand

Caledonian MacBrayne, the ferry operator, have published detailed statistics on passenger and vehicle numbers on each of their services for many years which provided an extremely useful dataset to establish the effect of factors such as population, and distance from Central Scotland (the main elements of the *Gravity Model*). In addition prices were obtained from past brochures and incomes from national statistics. The final model specified was

$$Q_{it} = aP_{it}^{\beta 1}\ Y_t^{\beta 2}\ N_i^{\beta 3}\ J_{it}^{\beta 4}\ \varepsilon_{it}$$

Where:

Q_{it} represents the passenger or vehicle numbers going to island i in year t
P_{it} represents the charge for passenger or vehicles going to island i in year t
Y_t represents the income of passengers in year t
N_i represents the resident population of island i
J_{it} represents the total journey time from the central belt to island i in year t

α is a constant, $\beta 1$, $\beta 2$, $\beta 3$, $\beta 4$ are demand elasticities and ε_{it} represents factors specific to island i in year t.

The separate models for passengers and vehicles were estimated using ordinary least squares and gave the following elasticities:

Table 13.7 *Passenger and vehicle elasticities*

	Price	*Income*	*Population*	*Journey Time*
Passengers	−0.58	1.30	0.68	−0.86
Vehicles	−0.87	1.91	0.78	−0.41

Tourism is an important element in demand for ferries to the islands and demand for those where it was most important (Arran, Mull and Skye) was underestimated. Conversely in Islay/Jura passenger numbers were substantially underestimated, in part because the more spectacular areas of Jura are currently difficult to access, whilst vehicle numbers were over-estimated. This peculiarity is the result of competition in earlier years with a private operator which has resulted in lower vehicle rates than usual for this length of journey. In policy terms the model suggests higher prices will generate higher revenue.

Assuming real prices and populations are relatively constant, a forecast of demand for Islay/Jura was generated assuming 3 different growth rates and a reduction in journey time of an hour. This gave an increase of 29.5 per cent over estimate (fit), 50.4 per cent over actual for passengers and 95 per cent over estimate, 54 per cent over actual for vehicles. These high impacts correspond surprisingly well with the initial report where demands were forecast to rise between 33 per cent and 66 per cent.

The choice model

On four islands Arran, Bute, Mull and Skye there were two ferry services, the first a lengthy direct service to the mainland and the second a much shorter, more frequent ferry service but with a much longer drive to and from the central belt. The proportion using the short service to each island over time was available in the data set as was the difference in prices, journey times and frequencies between short and long.

Because of the limitations of public transport, passengers not in vehicles had to travel on the long routes. There was, in effect, no choice for these passengers and hence the choice model was inappropriate.

The basic specification for the vehicles was:

$$Log_e\left(\frac{\Pr(Q_{Sit})}{\Pr(Q_{Lit})}\right) = \beta_1\,(P_{Sit} - P_{Lit}) + \beta_2\,(F_{Sit} - F_{Lit}) + \beta_3\,(J_{Sit} - J_{Lit}) + \varepsilon_{it}$$

Where, for each island i in year t

$\Pr(Q_{Sit})$ is the proportion of vehicles using the Short Sea route
$\Pr(Q_{Lit})$ is the proportion of vehicles using the Long Sea route
P_{Sit} is the Price of using the Short Sea route
P_{Lit} is the Price of using the Long Sea route
F_{Sit} is the frequency of the Short Sea route
F_{Lit} is the frequency of the Long Sea route
J_{Sit} is the total journey time using the Short Sea route
J_{Lit} is the total journey time using the Long Sea route
$\beta_1, \beta_2, \beta_3$ are coefficients to be estimated and ε_{it} is the stochastic term

Over 97 per cent of the variance was explained by the model with all coefficients highly significant.

It was thought that the through price to Islay using the short crossing and the Port Askaig ferry would only be slightly cheaper than the long route but would be substantially faster and more frequent. Applying the new journey times and frequencies suggested that just over 80 per cent of vehicles would switch to the short crossing; identical to the Intentions Survey result of 80 per cent.

Conclusion

The econometric model suggests that the numbers travelling to Islay/Jura would increase substantially and that the vast majority of both old and new clients would switch to the new route even if the existing route carried on as now. Of course losing 80 per cent of the business would put the long route into crisis and, one imagines, inevitable closure. The implications of closure on distillery traffic and on the road system in general resulted, as stated previously, in no action. Undoubtedly however with forecasts such as these it will be reconsidered again in the next decade.

CHAPTER SUMMARY AND REFLECTION

This chapter has shown how to set about getting demand forecasts for new and existing services, be they roads, airports, trains or boats. The methods range from simply 'asking customers' to sophisticated 'choice experiments'. There are limitations in the methods described in this chapter and a large number of more complex versions of the methods are available. However, just as fit does not necessarily equate to forecast quality, complexity does not necessarily equate to accuracy. Simple methods applied consistently and intelligently are likely, in the long run, to be more accurate.

CHAPTER EXERCISES

This chapter could end with several number-crunching exercises on forecasting; however, that is all they would be, exercises in number crunching. The basic theme of this chapter has been that we need to THINK when forecasting future transport trends and future demand, because it is through such thoughts that better forecasts are produced. Exercise 13.1 thus concerns a fictional case and asks you to consider the use of different forecasting approaches and the various data requirements necessary to produce an accurate forecast.

Exercise 13.1

A local transport authority is interested in developing Park and Ride facilities. In the short term this could be a dedicated bus service from an out-of-town shopping estate to the city centre. In the longer term there is the possibility of a new 'parkway' station, funded by the local authority. The station would provide both access to main-line services from the city and a park and ride facility to the city centre. The rail operator is worried about rush hour overcrowding and wants to institute a peak hour supplement for travellers. The local authority has extensive road and bus data on a peak/off peak basis and can access more data from outside the region. It has some data from other parkway rail schemes.

1 For the bus service an intentions survey has been suggested

- a) Suggest an appropriate sample frame
- b) Discuss the strata that might be used in a stratified random sample

2 Identify how we might forecast in five years time

- a) Vehicle flows at 8.30am on a Tuesday morning in October
- b) Vehicle flows at 3pm on a Saturday
- c) Why the month might be an important factor

3 Explain why a gravity model would be of little use in this problem

4 You are interested in building a model of the number of people who might switch to the bus

a) Identify the factors that you would want to include in your model
b) Discuss the associated data requirement and where such data might be found (or obtained)
c) Explain how a choice experiment might be used to assess the comparative impact of the price of the bus service and of bus priority lanes

5 Discuss in general how you might set about forecasting usage of the new station

a) By those going 'out' from the city on mainline inter-city services
b) By those using it as a park and ride facility going into the city
c) The impact of peak price supplements