Some economic contributions to transport demand modelling and forecasting with special reference to trip generation and car ownership

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SOME ECONOMIC CONTRIBUTIONS TO TRANSPORT DEMAND
MODELLING AND FORECASTING WITH SPECIAL REFERENCE
TO TRIP GENERATION AND CAR OWNERSHIP

Kenneth J. Button, BA, MA, MCIT

Thesis submitted in partial fulfilment of the requirement
for the award of Doctor of Philosophy of Loughborough University

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This thesis is concerned with the contributions economic theory and methods have made and may, in the future, make to the modelling and forecasting of transport demand. It emphasises that person movements are essentially determined by economic forces and thus require examination within an economic framework. While many of the arguments presented and points made are of general applicability within the transport field, particular attention is focused on the modelling of car ownership and, to a slightly lesser extent, of trip generation. In addition to the basic idea that economics should play a major rôle in transport demand analysis - which is possibly a more widely held view now than when much of the ground work for this study was conducted - the thesis pursues a number of other arguments.

Much of the recent research effort into travel demand has been of a highly mathematical and abstract kind. Quite clearly mathematics has an important part to play in this subject area, while abstraction is obviously an integral part of modelling and forecasting. Nevertheless, excessive mathematical sophistication or abstraction can divert attention from the main concern of modellers and forecasters; namely, the improvement of our understanding of a phenomena and the projection into the future of the course certain variables are going to take. The emphasis here is as much on the practical aspects of transport demand analysis and its uses, as upon the technical minutiae. A limited amount of theoretical mathematical modelling is indulged in but the theme is essentially pragmatic.
Equally, the thesis is concerned with ensuring that the forms of transport demand models developed are consistent in their underlying theory with the appraisal models which employ the final traffic forecasts. In essence the models examined here conform to the requirements of the current, best practice methodology employed in, for example, the appraisal of transport investment projects but, as is pointed out in the thesis, the implicit philosophy of public sector decision-making is slowly changing. Some thought is, therefore, given to the ways in which forecasting models may need to develop if they are to remain consistent.

A further theme, particularly in the context of car ownership and trip generation analysis, is the need to reflect important simultaneities in household decision-making regarding travel and related activities. The existing models of car ownership, in particular, at the national, regional and urban levels of analysis reveal serious defects both as tools in aiding understanding of car ownership decision-making and as an effective instrument in traffic forecasting. In addition, therefore, to a substantial amount of empirical work looking at and trying to improve single equation models, the thesis considers the possibility of constructing a simultaneous equation system integrating a number of demand and supply aspects of travel behaviour.

Finally, a major factor in household travel and car purchasing decisions is the quality of local public transport and, more generally, the level of accessibility. The thesis, therefore, throughout spends time exploring the ways in which this type of influence may be incorporated into travel demand analysis. While accessibility has long
been a central variable in modal choice and route assignment analysis, here the central focus is, once again, on trip generation and car ownership.

The thesis begins (Chapter 1) by considering the economic theory underlying travel behaviour and critically appraises the way that this theory has been incorporated into transport demand models. This general discussion is then elaborated upon in the rather more specific context of trip generation analysis (Chapter 2) and car ownership modelling (Chapter 3). The emphasis in these early chapters is rather more on the theoretical aspects with only a limited amount of empirical evidence being supplied. Following these introductory chapters, spatial variations in car ownership and (to a lesser degree) trip generation are examined drawing upon a considerable body of empirical evidence (Chapters 4 and 5). The study employs a variety of statistical procedures, all of which produce consistent results. This spatial analysis is followed by a consideration of the variables which influence car ownership decisions with particular attention being paid to the ways in which the explanatory variables may usefully be specified in applied forecasting work (Chapter 6). Finally, there is some discussion of the practical difficulties of selecting the appropriate forecasting framework and of the direction in which future work, especially in the field of car ownership modelling, may develop (Chapter 7). To supplement the seven main chapters, there are six, rather substantial, appendices.

In several ways this thesis differs from the standard work submitted for the degree of Doctor of Philosophy. Loughborough
University permits a member of the academic staff "to submit for a higher degree of the University a thesis or published work which must all relate to a common field". This volume, although in thesis form, contains a substantial amount of previously published material. In effect, it is a compilation of a series of previously published papers and fragments from monographs which have been subjected to a limited amount of up-dating (where appropriate) and brought together in a thesis format. The decision to do this rather than to offer a set of published papers in their original form and as they stand, rests upon a weighing up of several conflicting factors.

Quite clearly, bringing together a set of papers in this fashion involves additional effort - more physical than intellectual - not least because they were written over a period of a decade, and their contribution to 'knowledge' should possibly be judged in the context of when they were written. They were also written for a diverse set of audiences, ranging from economists and statisticians to planners and civil engineers, which means the emphasis and, indeed, vocabulary differs between the separate contributions. Additionally, they draw upon a very large number of sources and a wide range of studies and, in consequence, if a thesis is to be of reasonable size there must be selectivity in what is included and what is omitted. Therefore a substantial amount of material is, by necessity, and for practical expedience, not presented to the examiners.

Against these physical and technical disincentives to produce a thesis, however, one must set the notion that work in a "common field" should, in some way be linked and that these links are often
as important as the fragmentary contributions themselves. Consequently, a thesis offers the scope to present material in its academic context by highlighting the interrelationship of themes. It allows the various ideas and findings to be set against a broader background. It is, therefore, because it was felt important to show the interconnected nature of the ideas offered in a number of the author's publications that the thesis format was selected.

Where material offered in the thesis has been published elsewhere (and usually there has been some small amount of up-dating of this material) this is clearly indicated in the footnotes. Material previously published by the author has in fact been taken from one monograph, seven books of collected papers, a number of working papers and from the following refereed academic journals (and in some cases from more than one issue of a journal):

- Annals of Regional Science
- Applied Economics
- British Review of Economic Issues
- International Journal of Transport Economics
- OMEGA
- Socio-Economic Planning Sciences
- Statistician
- Three Banks Review
- Traffic Engineering and Control
- Transport Policy and Decision Making
- Transportation Planning and Technology
- Transportation Research
- Transportation Research Record
- Urban Studies
Some of the material drawn upon is of joint authorship (again this is made clear in the footnotes) but the author has, in all cases, tended to extract those components of joint papers or monographs for which he was primarily responsible. The vast majority of the work contained within the thesis is entirely of single authorship. On occasions, the author also references certain others of his publications not directly related to the main thrust of the thesis but as supporting evidence to some specific point - such material is really outside of the scope of the thesis and is being referred to in the same way as material by other, different authors.

Since the material presented in this thesis is the result of intermittent work over a long period it has obviously benefitted from discussions and correspondence with many people. It is impossible to list all who have helped but in particular the assistance of the following is gratefully acknowledged:- Alan Pearman, Tony Fowkes, John Tanner, John Bates and Mick Roberts. Additionally, the work has taken up a substantial amount of time and only the patience and forbearance of my wife, Elizabeth, has permitted its completion. Finally, Gloria Brentnall must be thanked for the excellent job she has done in producing the final typescript from a jumble of badly written, fragmented, multi-coloured scraps of paper.
CHAPTER 1

THE ECONOMIC THEORY OF TRAVEL DEMAND MODELLING

1.1 Introduction

It has been recognised for over a decade that travel can be treated as an 'economic phenomenon' and in particular that it is possible to forecast the future demand for passenger travel by utilising various econometric techniques. To the economist, travel is simply another good, perhaps a little more complex than most, and as such can be incorporated in a model of consumer behaviour. In this opening chapter, the underlying theory of travel demand models is described and discussed in the context of the current best practice forecasting procedures being used in transport planning.

We begin by describing traditional economic equilibrium theory in the setting of the transport market; briefly outlining 'neo-classical' notions of supply and demand and constructing from these a typical partial equilibrium system. Section three below is descriptive, giving some detail of the sequential analysis of the transport system which is currently used for forecasting purposes. Incorporated in the description are a few rudimentary criticisms of this method of analysis and this in turn leads to a more detailed discussion of the four basic sub-models in the following section.

This section goes on to contrast and compare the traditional sequential procedure and the 'explicit' demand models which have been devised in recent years, particular attention being paid to the abstract mode models which have been advanced since the publication of Kelvin Lancaster's article on "A New Approach to Consumer Theory". (2) The final section acts as a conclusion and summary.

1.2 Travel Demand Theory

1.2-1 Why Economic Theory?

Planners and policy-makers need to be able to evaluate the effects of alternative transport technologies and operating characteristics (3) and in order to do this they need an explicit methodology for forecasting the consequences of modifications to the transport system. Their requirements place certain restrictions on the forecasting model which is eventually adopted. It is necessary that the model is structural, describing the inter-relationships between relevant and predictable variables which influence the demand for, or performance of, the transport system. Economic theory provides a framework within which such a structural model may be developed and, in addition, provides a valid set of rules within which it operates. These rules provide a dynamic element to


2.
the model which is vital if we are to be able to estimate the effects of input changes through time and so understand the sensitivity of travel demand to variations in certain policy variables as well as the more traditional land-usage variables.

At a rather more fundamental level, we need to recognise that in postulating any travel forecasting model, we are hypothesising about human behaviour. Early attempts to build model systems based upon physical characteristics and using mechanical extrapolation procedures failed to produce reliable predictions precisely because they took no or, at least, insufficient account of the human element. Travel (as opposed to the transportation of goods) is undertaken by people and it is their varying response to certain stimuli which creates variations in travel demand; it is not the stimuli themselves. It is not the physical conditions of a zone which determines the pattern of travel which originates within it but rather the inhabitants' responses to these conditions. A forecasting model needs to be capable of explaining the variations found in individual responses to these physical characteristics; in other words, explain why two people confronted with the same physical environment act differently. Economics provides such a behavioural theory, explaining differences in individuals' responses by reference to their economic, in addition to their physical, environment, taking price, income and taste as the all-important explanatory variables. In this way, it is possible to explain why two areas, identical in terms of land-usage, can exhibit quite different travel demand patterns.
This movement towards what has become known as 'behavioural modelling' is not without its difficulties and, as we see later, foremost among these is that of defining the behavioural unit. It is clear that in adopting such an approach, we need to assume that the best way to explain behaviour en masse is to study the comparable aspect of human behaviour at a more disaggregated level; the problem is then one of deciding whether it is the individual, the household or some other unit that we need look at.

1.2-2 Equilibrium Theory

Travel forecasting requires a process of equilibrium between system performance functions (in which performance varies with trip volume) and demand functions (in which trip-making varies with system performance). (4)

A demand function is defined, in the simplest terms, as a dependent relationship between the amount of a particular good demanded and its price, the relationship being negative in all but a few questionable instances. (5) The usual accompanying proviso stipulated by economists is that other things must remain equal (the ceteris paribus condition); namely, that the tastes of consumers, their income and the price of all other goods has remained unchanged. (6) Changes in these latter variables 'shift' the demand curve influencing the quantity demanded at any price.


6. Ibid., p.97.
level. The responsiveness of the quantity of the good demanded to changes in the explanatory variables is defined in terms of elasticities, (7) e.g. price, income and cross-elasticities indicate the responsiveness of the quantity demanded to changes in the good's price, the consumer's income and the price of other goods respectively.

Turning to look at travel demand functions specifically, we find that a number of modifications need to be made to the basic theory outlined above to allow for the peculiarities of the 'good'. The demand for travel is 'derived' due to the complementary nature of travel in the consumption of other goods. In a market economy, transport demand arises as the result of utility maximisation by households and/or profit maximisation by firms. However, it is seldom demanded for itself (except by joy-riders) but rather as a derivative of buying some other good or service. It is for this reason that regional and urban economists treat travel as an impedance factor hindering perfect mobility. (8) They argue that a person in zone A desiring to undertake some activity in zone B will do so only if the joint cost of travel and that of purchasing the final activity at zone B is exceeded by the utility obtained. Similarly, for travel demand estimation, one must consider not just the price of travel itself but also the price of the commodities available at the journey's end.

A further difficulty is that in some instances we are dealing with an inferior good, the result of it being subject to a negative

7. Ibid., pp.102-113.

8. For example, see H.W. Richardson: - Regional Economics (Weidenfeld and Nicolson), 1969.
income effect (an effect, however, which is not sufficient, save in exceptional instances where we are dealing with a 'Giffen Good'\(^9\)) to outweigh the consistently positive substitution effect). It is common knowledge that a rise in income tends to reduce the use a family makes of public transport; indeed, this is becoming an increasingly important problem in a society of ever-increasing affluence but only limited space to accommodate the growing demands of the private motorist.

These two complications obviously need to be incorporated in any explicit model, but for the moment we push them to the backs of our minds and proceed to develop a very basic equilibrium equation system based on Marshallian theory. In the model, we consider a transport system (T) and its associated socio-economic variables (A) and for these we can find the equilibrium flow in the transport market by devising a series of related functions.\(^{10}\) As stated earlier, the first of these relates the demand for travel to the transport system variables and the associated socio-economic variables, i.e.

\[
V = D(L, A) \quad \text{Eq. 1.1}
\]

where: \(V\) is the volume of traffic flow

and \(L\) is the level of service experienced at that flow.

The level of service can be taken loosely as our price variable and as such it is possible to decompose it into travel time and travel cost components. Each of these is dependent upon both the volume of

---


traffic flowing and the transport system itself (Kraft and Wohl\(^{(11)}\)) also make the travel cost component dependent upon a 'pricing policy' variable but this seems an unnecessary complication at this stage) and hence it is fairly clear that as the volume of traffic increases, there must be a compensating expansion of the transport network or else the consequential reductions in speed will result in greater travel times and probably rises in travel costs (in other words, an outward shift in the demand curve for travel will increase its price unless countered by a balancing shift in the supply schedule). As the level of service is effectively the supply of transport available for consumption in certain predetermined conditions we can express a second function in the form

\[
L = S(V, T)
\]

Once this has been determined, we can solve for the equilibrium flow \(F_0\) which is consistent with these supply and demand functions and

\[
F_0 = (V_0, L_0)
\]

[in other words, \((T, A) \rightarrow F = (V, L)\)]. A simple diagrammatic presentation is given in Figure 1.1.

The Marshallian type model outlined above is a useful starting point for transport analysis but its very simplicity tends to obscure many of the important structural dimensions of a trip-maker's behaviour. The single equations presented are in reality multiple functions, the unique value variables being replaced by vectors and matrices. The demand function (equation 1.1) varies between different zone pairs, person types and journey purposes. In addition, the consumer considers many attributes of the transport system (e.g. on-vehicle travel time, waiting time, money costs, comfort, service frequency, etc.), hence \( L \) needs to be replaced by a vector of service characteristics. Similarly, when looking at the supply situation (equation 1.2), it is clear that each 'link' in the network has its own function which is, in turn, dependent upon a vector of service attributes.
Solution of the equation system is also extremely complex as the service level (L) is itself dependent upon the route selected and, at a further level of disaggregation, the service over each route becomes a function of the transport service over its component links. This leads to the further difficulty that the volume of traffic over each link is itself influenced by the volume of traffic over it but this, as an additional complication, will be composed of traffic moving between numerous different zone-pairs. Even when a solution is obtained and an equilibrium flow calculated, there is no guarantee that it will be unique, the flow pattern being dependent upon the assumptions employed.

1.3 The Sequential Approach to Travel Forecasting

1.3-1 Introduction

The empirical work carried out by transportation systems analysts in this country has been characterised by their use of a series of sub-models to describe the travel demand function; this contrasts sharply with the explicit model suggested by the theory set out above. The development of this sequential approach over the last fifteen years represents the first large-scale application of modern systems analysis to problems in the non-military sector. The underlying hypothesis of this method is that it is possible to reach a flow equilibrium via a series of successive approximations and thus reduce the computational problems involved for only a minimal loss of accuracy. The approach is of particular use in representing trip demands over complex networks with a large number of substitute destinations, modes and routings; a situation common.
to most urban areas. The sub-models initially determine the
total number of trips generated and then proceeds to allocate
them to destinations, vehicle modes and ultimately routes (see
Figure 1.2).

![Diagram of traffic modelling process]

Figure 1.2

The stages in the sequential approach
to traffic modelling

1.3-2 Trip Generation

The trip generation stage of the planning process determines
the scale of the aggregate demand for travel originating in each
of the study zones and the aggregate travel attracted to each
study zone (trip attraction). The 1953 Detroit study\textsuperscript{(12)} set the
pattern of early analysis by employing zonal-based regression models
with the physical characteristics of the area as explanatory
variables. Trip generation was seen as the first stage of a

\textsuperscript{12} Michigan State Highway Department: - \textit{Detroit Metropolitan Area
Traffic Study}, 1953.
process linking land-use to the movement of goods and persons. This rather mechanical approach was quickly abandoned and the inclusion of socio-economic variables signalled the recognition of the importance of the entire urban environment. The strong similarity still to be seen between the early models and all subsequent ones is the reliance placed upon exogenous variables as the sole determinants of aggregate travel demand; the justification for such models is subject to some discussion later (see Chapter 2).

1.3-3 Trip Distribution

The second stage of the forecasting sequence is the distribution of the trips generated between the various origin-destination pairs. A number of techniques have been developed which, in general, can be broken down into two categories: the analogy or growth factor models and the simulation models.

The first group contain those procedures which simply extrapolate the existing pattern of travel into the future by attaching some form of expansion factor based upon likely population, car-ownership and economic trends. Early attempts at using a single growth factor across the board gave way to a wide range of modified procedures of greater complexity to allow for variations in the expansion rates within the study area. In the United States, 'Fratar' models (13) were widely used in studies carried out in the late 1950s and 1960s to circumvent the shortcomings of the pioneering

average and uniform factor procedures, the modification allowing for the effect of the location of a given zone with respect to all other zones. In Britain, the simpler technique advocated by Furness\textsuperscript{(14)} in the early 1960s was preferred. This model involves an iterative procedure which adjusts the cells of the data matrix by row and column factors until the row and column sub-totals correspond to the zonal trip ends calculated in the previous stage. The cell entries are the base year inter-zonal trips and these are iterated to total origin and destination forecasts for each zone at the design year.

Despite the improvements made, the limitations of the analogy techniques remain. All growth factor models require a full origin-destination matrix which is frequently unobtainable due to the financial and time constraints confronting the analyst. On the theoretical plane, the technique is unable to cope with 'development zones' where there is no existing trip distribution pattern to be balanced against future trip totals. In addition, growth factoring, by its very nature, is incapable of representing changes in trip distribution resulting from variations in future zonal accessibility, changes occurring if journey times (costs) are improved by new roads. In his later work, Furness tries to overcome these problems by suggesting that 'time indices' should be used instead of observed trips as initial cell entries\textsuperscript{(15)} which effectively introduces time as an accessibility factor in the distribution pattern.


This modification is moving away from the growth factor school towards the synthetic models we now turn to.

Simulation models are varied in character but discussion of two, the opportunities method and the gravity model, give a basic outline of the approach. Opportunities models are divided into two types: those considering intervening opportunities and those concerned with competing opportunities. Both are typified by their application of probability theory. The intervening model assumes that the number of trips from an origin to a destination zone is proportional to the number of intervening opportunities. In this way, it is assumed that the traveller will consider each opportunity in turn and has a definite probability that his needs will be satisfied. The competing model uses a different probability function with the probability that a trip will go to a particular district dependent upon the ratio between the trip opportunities in the district and its competing opportunities.

Whilst the opportunities approach has its foundation in mathematical modelling, the gravity model is based upon analogies between spacial interaction in geography and spacial interaction in classical physics. Gravity models have been used extensively in location theory and regional studies since the late 1920s (16) but it was not until about twenty years ago that they came into common usage in travel analysis. Although various forms have been adopted, the distinguishing feature of the gravity model is that it can be

16. Early work being particularly associated with W.J. Reilly, e.g. W.J. Reilly:- Methods for the study of retail relationships, University of Texas Bulletin, No.2944, 1929.
decomposed into (a) terms which measure the mutual attractiveness of origins and destinations and (b) terms which measure the effect of impedance imposed by the transportation system. In early work, attractions were specified in terms of population size but in more recent studies a multiplicity of factors are included frequently varying with the journey purpose under consideration. Similarly, the crude notions of impedance being simply a function of distance has given way to ideas of 'generalised costs'.

The sequential nature of the planning process requires that the results of the distribution stage agree with the trip ends estimated and in order to secure this, iterative procedures have been introduced. If we take the gravity model, the basic idea can be demonstrated by consideration of a number of constraints imposed on the distribution. If we assume that both the origin and destination totals are required to conform to the estimates provided by the trip generation model, then a double constraint model is

17. Generalised cost functions incorporate variables reflecting the non-monetary costs of trip-making. For example, the South-East Lancashire, North-East Cheshire study employed a cost function of the form:

\[ c_{ij}^K = a_1 t_{ij}^K + a_2 e_{ij}^K + a_3 d_{ij}^K + p_j^K + \delta^K \]

where:
- \( c_{ij}^K \) is the generalised cost of moving from i to j by mode K
- \( t_{ij}^K \) is the travel time between i and j by mode K
- \( e_{ij}^K \) is the excess time (waiting time for public transport, etc.) involved in travelling between i and j by mode K
- \( d_{ij}^K \) is the distance between i and j using mode K
- \( p_j^K \) is the terminal cost at j (e.g. parking charge)
- \( \delta^K \) is a modal penalty factor to allow for quality differences between mode K and other modes (e.g. in terms of comfort)
employed demanding that:
\[ \sum_j T_{ij} = O_i \]  
\[ \sum_i T_{ij} = D_j \]

where:  
- \( T_{ij} \) is the number of trips between zone \( i \) and zone \( j \);  
- \( O_i \) is the number of trips originating in zone \( i \);  
- \( D_j \) is the number of trips destined for zone \( j \).

A respectable version of the gravity model duly constrained can then be supplied by the 'interactance model' equation:
\[ T_{ij} = \frac{O_i D_j A_i B_j f(c_{ij})}{[\sum_j D_j B_j f(c_{ij})]^{-1}} \]  
\[ T_{ij} = \frac{O_i A_i B_j f(c_{ij})}{[\sum_i O_i A_i f(c_{ij})]^{-1}} \]

where:  
- \( f(c_{ij}) \) represents some generalised cost function of travelling between zone \( i \) and zone \( j \);  
- \( A_i = \left[ \sum_j D_j B_j f(c_{ij}) \right]^{-1} \)  
- \( B_j = \left[ \sum_i O_i A_i f(c_{ij}) \right]^{-1} \)

These latter two expressions are often referred to as 'fudge factors' but they can quite sensibly be interpreted as inverse measures of accessibility and, indeed, Arrowsmith has argued "that they should be defined as inverse indices of accessibility to available opportunities". (18) Frequently one or other of the constraints is relaxed in order to increase the available degrees of freedom, but in doing this the analyst is removing his guarantee that the total trips distributed to, say, zone \( j \) will equal the trip ends predicted.

Recent work on 'social physics' has resulted in the introduction of statistical mechanics into trip distribution modelling especially the useful hypothesis generating technique of maximising entropy functions (trip distribution being seen as having the same basic structure as a "closed physical system in thermal equilibrium"(19)). Initial work by Cohen(20) has recently been extensively improved upon by A.G. Wilson(21) who has demonstrated that both the gravity and opportunities type models can equally well be derived from statistical mechanics as from Newtonian Physics. Although this new approach opens fresh fields to the transport systems analyst, it should be borne in mind that entropy maximisation can only generate hypothesis and that empirical verification is needed before they can be accepted for decision-making purposes. (22)

A more direct economic approach to both opportunities and gravity models is that of Cochrane. Using micro-economic theory and making a number of explicit statistical assumptions, he demonstrates that simulation models can be derived as the principle


"that trip-makers choose the trips which provide the greatest net benefit for them as individuals, and that the trip distribution pattern reflects the overall probability of particular trips being chosen on this basis".\(^{(23)}\) In the case of the gravity model, it is assumed that the probability of a trip-maker from one zone travelling to another will depend upon the probability of the net benefit in the second zone being greater than in any other zone.

1.3-4 Modal Choice

Modal split involves the allocation of inter-zonal trips to particular vehicular forms. Planners are particularly interested in the split between private motor car travel and that by public transport and consequently models have been designed to that end. The modal choice models can be classified as either a trip-end or trip-interchange type. The former have been widely used in highway-orientated origin and destination studies where the concentration is on motor car travel with public transport being treated as a residual which may be subtracted from the trip end predictions before the assignments are made. The obvious limitation of such an approach is that the analysis concentrates entirely on factors such as income and car-ownership to the exclusion of any consideration of the relative attractiveness of the various modes; this clearly conflicts with traditional economic theory.

The interchange models, in contrast, have been developed for public transport feasibility studies and consequently concentrate on the comparative time, cost and service differentials between competing modes. In order to enable valid comparisons, it has been found necessary to attempt to place some value on the various components of travel time and service quality in order that these components of the generalised cost function can be made commensurable with fares and other truly monetary costs. Many interchange models include an explicit time evaluation procedure but the wide range of values that they have obtained seem to suggest that no really satisfactory modal choice model has been developed to date. (24)

1.3-5 Network Assignment

Once the projections of the inter-zonal trips by mode have been calculated, then they need to be allocated to links in the transport system. This is done by comparing the characteristics of the links in the network and assigning traffic to those which appear the cheapest in terms of journey times and travel costs. Early approaches used diversion curves, a technique similar to the interchange model developed for forecasting modal split, but with the introduction of minimum path algorithms in the 1950s, more sophisticated programming procedures became available. These assignment models are based on the economic criterion that the

traveller selects the path that will minimise his travel time (or cost). (25)

A major problem in this stage is to constrain the traffic allocated to any link to the capacity of that link. If the capacity constraint is omitted, then an "All or Nothing" assignment results and no allowance is made at all for the congestion which accompanies increased volume. In reality, travellers use all routes, both the 'cheap' and the not so 'cheap', especially when cost differences are small. The introduction of capacity constraints avoids this problem by adjusting link speeds as the assignment proceeds and congestion increases. Whether this is in fact sufficient or whether the capacity restrictions will have feedback effects on trip generation, distribution and modal choice is a matter discussed in the next section.

1.3-6 A Critique of the Sequential Approach

The first point to emphasise is that the traditional forecasting sequence is not concerned with the demand for travel per se but rather with the level of utilisation of transport facilities. This situation results from the practical restriction which requires one to look at, what we might loosely call, effective demand, any other approach defying calibration. Despite this, the procedure still examines an interaction between demand and supply schedules, although whether the conventional cross-sectional study

can yield any information on the underlying demand relationships is less certain. (26) The sequential approach represents an attempt to analyse various specific dimensions of the usage of the transport system rather than travel demand in its strictest sense.

The traditional approach is an attempt to build a triangular or recursive equation system with only a single direction of causation. (27) We can see this clearly if the four equations are restated in their most basic form. If we continue to assume that trip generation and attraction are determined solely by exogenous factors, then our initial equations can be written simply as:

\[
T_i = \mathcal{F}(A_i) \quad \text{Eq. 1.9}
\]

and

\[
T_j = \mathcal{F}(A_j) \quad \text{Eq. 1.10}
\]

where: \(T_i\) and \(T_j\) represent the traffic generated by zone \(i\) and the traffic attracted to zone \(j\) respectively;

\(A_i\) and \(A_j\) are the socio-economic characteristics of zones \(i\) and \(j\).

Similarly, we find that the trip distribution model may be expressed as:

\[
T_{ij} = \mathcal{F}(A_i, A_j, L_{ij}, T_i, T_j) \quad \text{Eq. 1.11}
\]

where: \(T_{ij}\) is the traffic moving between zones \(i\) and \(j\);

and \(L_{ij}\) is the impedance to travel between zones \(i\) and \(j\).

In the modal split stage, allowances must be made for the predicted distribution and consequently it may be summarised as:

---


27. For an outline of the rationale of recursive equation systems, see H. Wold and Z. Jureen: - *Demand Analysis* (Wiley), 1953.
\[ T_{ijm} = F(L_{ijm}', L_{ijm}'', T_{ij}') \]  

Eq. 1.12

where: \( T_{ijm} \) is the traffic between zones \( i \) and \( j \) using mode \( m \);

\( L_{ijm} \) represents the attributes of mode \( m \) when taking traffic between zones \( i \) and \( j \);

and \( L_{ijm}' \) represents the attributes of other modes available for use between zones \( i \) and \( j \).

Finally, we have the assignment stage, where traffic is allocated to specific routes in the following generalised manner:

\[ T_{ijmp} = F(L_{ijmp}', L_{ijmp}'', T_{ijm}') \]  

Eq. 1.13

where: \( T_{ijmp} \) is traffic using route \( p \) when travelling by mode \( m \) between zones \( i \) and \( j \);

\( L_{ijmp} \) and \( L_{ijmp}' \) represent the characteristics of path \( p \) and alternative paths respectively.

Hence, the initial calculation of \( T_i \) and \( T_j \) based on exogenous factors reduces the system to a recursive model of the form:

\[ T_i = F_1(T_i', T_j', \ldots) \]  

Eq. 1.14

\[ T_{ijm} = F_2(T_{ijm}', \ldots) \]  

Eq. 1.15

\[ T_{ijmp} = F_3(T_{ijm}', \ldots) \]  

Eq. 1.16

In reality, the system exhibits complex simultaneous relationships not catered for in such a sequence, hence the recursive approach is best thought of as an initial approximation which requires supplementary iterative processes to improve the internal consistency of the model and the accuracy of the forecast flows. To obtain reasonable estimates from the generation, distribution and modal choice stages, one needs to know \( L_{ijmp} \) for all \( i, j \) and \( m \) but this only becomes available following traffic assignment when the supply conditions on the various network links are introduced into the model.
The predicted value of $L_{ijmp}$ may differ quite substantially from those assumed in the previous stages of the equation system and to make allowances for the changes brought about by the supply factors will require some form of feedback mechanism. In practice, no such procedure is included in the forecasting package and even if one were, Manheim argues, there is no guarantee that a unique equilibrium flow will result. (28) The effect of this omission is likely to be of particular importance in areas where congestion prevails as the initial travel times (or costs) are probably going to differ substantially from the equilibrium times which may seriously affect the accuracy of the forecasts. (29)

Even if an iterative procedure is adopted, the weight of calculations involved in its calibration may still prevent complete internal consistency in the equation sequence. To ensure that one has full consistency, it is necessary that: (30)

(a) The level of service, $L$, enters at each stage in the sequence including generation unless it is explicitly found to be superfluous.


29. The model developed by the G.L.D.P. does incorporate some feedback from the assignment stage where overloadings occur but the linear programming procedure employed only related back to trip distribution. A further limitation on the effectiveness of this process is that the size of the model prevented more than three iterations being performed. For more details, see B.V. Martin: - Transportation studies: a review of results to date from typical areas - London, Proceedings of the Transportation Engineering Conference, 1968, pp.3-13, and section 2.3 of Chapter 2.

(b) The same attributes of service should enter at each step unless the data indicates otherwise.

(c) The same values of the level of service should influence each sub-model.

(d) The level of service provided by every mode should influence the demand to some degree.

Non-fulfilment of these conditions is accompanied by inadequate coverage of service even when allowance is made for its influence; perhaps a reflection on the inadequacies of present data collection procedures.

A rather more practical criticism is that although the sequence allows 'goodness of fit' tests to be performed on each of the individual sub-models, it prevents such tests being applied to the set of equations as a whole. This limitation is likely to be especially great when iterative procedures are employed as there will be no way of telling when sufficient iterations have been performed to yield an acceptable approximation to the survey data.

1.3-7 Explicit Demand Models

The criticisms of the urban transportation modelling sequence have led to the development of explicit demand models which either combine all the sub-models of the sequence or a number of them. These models are usually extensions of either the distribution or modal split stages, frequently combining all the steps of the traditional system with the exception of generation and attraction calculations which are performed separately, their independence
allowing their use as constraints. The basic idea is that the equilibrium flow is reached by estimating "from the inside out" - as opposed to the 'outside in' approach suggested by the traditional sequence - by performing a direct calculation of the demand for the flow on each link in the network. Returning to our simple model, \( T_{ijmp} \) is estimated directly according to the explicit model and any higher level aggregations are obtained by a series of simple summations, i.e.

\[
T_{ijm} = \sum_p T_{ijmp} \tag{Eq. 1.17}
\]

\[
T_{ij} = \sum_m T_{ijm} \tag{Eq. 1.18}
\]

\[
T_i = \sum_j T_{ij} \tag{Eq. 1.19}
\]

The generation, distribution, modal split and assignment stages are therefore combined in the single general equation:

\[
T_{ijmp} = F (A_i, A_j, L_{ijmp}, [L_{ijmp}, p]_{m'\neq m}, [L_{ijmp}, p', p]) \tag{Eq. 1.20}
\]

In papers produced by Kraft and Wohl (31) and Domenich, Kraft and Valette (32) a single econometric demand model is developed in which price and other service characteristics affect not just modal split (with origins and destinations determined) but influence, in addition, the total level of travel. Once travel demand has been stratified by trip purpose, an equation is fitted to zonal interchanges by mode using not just network characteristics as explanatory variables but also travel time (and cost) and economic variables.


Although the ideas advanced have a strong intuitive appeal, the actual model used has a number of computational drawbacks. A high degree of multicollinearity means that parameter estimation requires some form of constrained multiple regression with subsequent demands for additional a priori information to ensure 'correct' magnitudes and signs for the demand elasticities and cross-elasticities. This requirement tends to result in poorer data fits than are obtained from conventional models; a fact supported in an empirical investigation of Boston by the authors.

Wilson (33) has produced a model combining distribution, modal split and assignment which is subject to pre-determined trip end estimates and to a budgetary constraint. The relatively simple constraint developed for a combined distribution and modal split estimation allows for n person types having different per capita expenditure on travel, $C^n$, and may be represented as:--

$$\sum_i \sum_j \sum_{m \in M(n)} T_{ij} c_{ij}^m = C^n$$

Eq. 1.21

where: $M(n)$ is the set of modes available to person type n;

$m \in M(n)$ denotes one such mode;

and $\Sigma$ is the summation over all modes, $m \in M(n)$

It is clear, however, that the introduction of numerous paths as well as modes will considerably complicate this. Peacock (34) questions the usefulness of a monetary constraint and suggests its replacement by one based upon time budgets. He supports his


contention with references to the extensive literature now becoming available on time budgeting (35) and the argument that "not only is time the one resource that is equitably distributed over the entire population, but empirical studies suggest that time budgets are effectively constant at quite a disaggregated level". (36) Although Peacock's modification may improve on the theoretical foundation of the model, it does not surmount the obstacles inherent in such an approach as suggested by Wilson (37) himself, namely its computational complexity and demands for sophisticated data.

A more promising line of analysis is supplied by the theory of consumer demand developed by Lancaster and its subsequent adoption in 'abstract mode models'. (38) Lancaster argues that people do not demand goods for their own sake but for the "characteristics" they possess; these characteristics giving rise to utility. The important modification to conventional theory is that the consumer is now regarded as deriving utility from characteristics, while commodities are the suppliers of these characteristics in varying quantities and proportions. In this form, utility maximisation becomes a non-linear programming problem which, if we take the standard choice situation facing the consumer in a free market, with a linear budget constraint, will take the general form:

38. Lancaster, op. cit. It is this theoretical philosophy which forms the basis of the local car ownership modelling in Chapter 5.
Maximise \( U = U(z) \)  
Subject to \( z = g(x) \)  
\( px = Y \)  
\( x \geq 0 \)  
\( z \geq 0 \)

where: 
- \( z \) is a vector whose elements represent the quantities of various characteristics;
- \( U \) is an individual's ordinal utility function on characteristics \( U(z) \);
- \( x \) is a vector whose elements represent the quantities of various commodities;
- \( p \) is the vector of corresponding prices;
and 
- \( Y \) is the level of income.

Lancaster's innovations are two-fold. Firstly, he advances the idea that the consumer obtains or derives his utility from the characteristics (or attributes) of the goods rather than from the goods themselves. In this way, commodities are seen as producing attributes in varying amounts and proportions; a situation analogous, but not identical, to production theory with goods viewed as inputs into a process in which the characteristics represent the outputs.\(^{39}\) The second advance is the statement of consumption theory in terms of an objective efficiency frontier (on which the rational man will consume) with the actual consumption of each individual resulting from a subjective decision to consume at a particular point on the frontier (the 'preferred position').

\(^{39}\) The primary distinction between consumption and production technology is that while the former typically involves a single input (a good) and joint output (the attributes), the latter tends to have joint inputs and a single output. It is clear that in this way a good may have more than one characteristic and a single characteristic may be obtained from more than one good.

27.
Effectively, this distinguishes between efficiency substitution effects which alter the shape of the frontier in response to, say, a change in relative prices and a notion of revealed preference as indicated by a person's selected consumption combination on the frontier.

The importance of this approach in the study of travel demand is that trips, on one hand, and all remaining goods, on the other hand, represent what Lancaster describes as "intrinsically unrelated commodity groups". Now, as trip taking only provides travel-orientated characteristics and trips provide no other attributes than trip-orientated attributes, changes in prices of goods other than travel have no effect on the efficient combination of trips. This advantage, coupled with the basic premise implicit in the theory that the demand for any good is derived from the demand for its attributes, has led to the adoption of Lancaster's approach in travel demand analysis, especially in the determination of modal split and distribution-based models.

The theoretical usefulness of Lancaster's model is apparent if we concentrate on the economic derivation of the gravity model of spatial interaction. Although it is possible to derive the gravity law from either Newtonian or social physics, the desire to account for the spatial aspects of economic phenomena has led to attempts at constructing spatial interactance models directly from economic principles. Niedercorn and Bechdolt applied

traditional utility maximisation principles to trip-making functions by maximising the utility derived from interaction by individuals living in a base zone and travelling to all surrounding zones. Use of Lagrange Multipliers enabled either a money or time budget constraint, whichever appears the most appropriate, to be applied.

In ensuing papers, (41) it was argued that the approach adopted by Niedercorn and Bechdolt placed its entire emphasis on the trip and excluded its attributes. (It was in effect a direct rather than a derived demand model.) A simple way of avoiding the rather unconvincing hypothesis that utility is a direct function of the number of trips undertaken is to employ the basic linear programming approach outlined above. If we assume that there are two characteristics \([C_1 \text{ and } C_2]\) and three types of trip \([T_1, T_2, \text{ and } T_3]\) where there is a one-to-one correspondence between trips and activities (hence one type of trip gives rise to a single activity vector representing a bundle of positive \(C_1\) and \(C_2\)), then we can construct the efficiency frontier ACB in Figure 1.3. The individual concerned, call him K, will select his bundle of characteristics from those available on the frontier, the attainable attributes being determined if the whole of the available budget is spent on \(T_1, T_3\), and \(T_2\) respectively (\(A, C\), and \(B\) representing these attainable points). If the price of trip type \(T_3\) rose so that the budget only allows some quantity below \(C'\) to be purchased, say \(C''\),

then the efficiency frontier for consumption becomes AB and the rational consumer will make a selection on this curve.

![Figure 1.3](image)

This method of analysis, although consistent in itself, does not provide a very useful model. It gives the utility maximising combination of trip characteristics of different types of trips from the origin to a given destination, whilst the gravity model deals with the utility maximising number of trips of a particular type (per unit time) taken by individuals moving between a base and all other zones. The situation may be retrieved, however.

A trip characteristics vector may be associated with each destination zone to which our individual, K, takes trips from base zone i. The slope of the characteristics vector of trips by K from i to each destination is defined by the relationship between $v_{ij}^{(h)}$ (h=1, 2, ..., p) and the magnitude of each vector by
where: $v_{ij}^{(h)}$ is characteristic $h$ per trip by individual $K$ from $i$ to destination zone $j$;

$K_{ij}^{T}$ is the maximum number of trips that can be taken by all individuals from origin $i$ to destination $j$, per unit time, given $K_{Mi}$ for each of $m$ individuals and $z_{ij}$;

$K_{Mi}$ is the money that $K$, located at origin $i$, is willing to spend on travel per unit time;

and $z_{ij}$ is the cost per trip from origin $i$ to destination $j$ (it is the explicit monetary form of the general impedance cost $L_{ij}$ given above).

This defines the co-ordinates of the end points of a set of $n$ trip characteristics vectors, one for each destination, as

$$
\begin{bmatrix}
\frac{K_{i1}}{z_{ij}} v_{ij}^{(1)} \\
\vdots \\
\frac{K_{in}}{z_{ij}} v_{ij}^{(p)}
\end{bmatrix}
= \begin{bmatrix}
K_{ij}^{T} v_{ij}^{(1)} \\
\vdots \\
K_{ij}^{T} v_{ij}^{(p)}
\end{bmatrix}
\quad \text{for all } j=1,2,\ldots,n \quad \text{Eq. 1.28}
$$

In general, the trips by $K$ from $i$ to each of the $n$ destinations can be transformed into a set of $p$ trip characteristics by

$$
\begin{bmatrix}
C_{ij}^{(1)} \\
\vdots \\
C_{ij}^{(p)}
\end{bmatrix}
= K_{ij}^{T}
\begin{bmatrix}
v_{ij}^{(1)} \\
\vdots \\
v_{ij}^{(p)}
\end{bmatrix}
\quad \text{for all } j=1,2,\ldots,n \quad \text{Eq. 1.29}
$$

where: $C_{ij}^{(h)}$ is the amount of attribute $h$ consumed by individual $K$ in making $K_{ij}^{T}$ trips from origin $i$ to destination $j$ per unit time;

and $K_{ij}^{T}$ is the number of trips taken by $K$ from $i$ to destination $j$ per unit time.
The utility of K at origin i from interacting with people and things at all of the destination zones per unit time may be expressed as

\[ U_i = a \left[ 1, \ldots, 1 \right] \left[ \begin{array}{c} \sum_{h=1}^{p} \sum_{j=1}^{n} \frac{P_j}{aP_j} C_i^{(h)} \\ \vdots \\ \sum_{h=1}^{p} \sum_{j=1}^{n} \frac{P_j}{aP_j} C_i^{(p)} \end{array} \right] \]

\[ = a \sum_{h=1}^{p} \sum_{j=1}^{n} \frac{P_j}{aP_j} C_i^{(h)} \]

where: 
- \( P_j \) is the population of destination j;
- \( K_i \) is the total net utility of individual K at i of interacting with persons (or things) at all destinations per unit time;
and  
- a is a constant of proportionality.

The budget constraint affecting K at origin i is

\[ K_i^M \geq \sum_{j=1}^{n} K_i^T z_{ij} \]

To maximise his utility subject to his budget constraint, K would maximise

\[ U_i^3 = a \sum_{h=1}^{p} \sum_{j=1}^{n} P_j \left[ \frac{K_i^{(h)}}{aP_j} \right] - \lambda \left( \sum_{j=1}^{n} K_i^T z_{ij} - M_i \right) \]

where the first order conditions for utility maximisation are

\[ \sum_{h=1}^{p} \frac{\partial f(K_i^{(h)}/aP_j)}{\partial K_i^{(h)}} \left[ \frac{dC_i^{(h)}}{dK_i^{(h)}} \right] - \lambda (\sum_{h=1}^{p} \frac{\partial f(K_i^{(h)}/aP_j)}{\partial K_i^{(h)}}) = 0 \]

\[ \sum_{h=1}^{p} \frac{\partial f(K_i^{(h)}/aP_j)}{\partial K_i^{(h)}} \left[ \frac{dC_i^{(h)}}{dK_i^{(h)}} \right] = 0 \]

for all \( j=2, 3, \ldots, n \)

\[ \sum_{j=1}^{n} K_i^T z_{ij} - M_i = 0 \]
This gives the general form derived from maximising the utility function without stating its explicit form. Niedercorn and Bechdolt (42) also demonstrated, using both logarithmic and power utility functions of trip-making, that the traditional factors affecting social phenomena occurring between geographical areas can still be isolated as origin, destination and linkage influences, as with the conventional gravity model. It is also possible to incorporate a time budget constraint where this is felt to be operative, e.g. when considering middle-class travellers, money is only likely to be a constraint in inter-urban travel, whilst the time budget is likely to be the limiting factor for within zone travel.

The theoretical model set out above can be extended to cover modal choice and route selection by the introduction of additional sub and super scripts. This obviously leads to increased complexity and difficulty in determining what the important characteristics are (this is a problem for anyone attempting to apply Lancaster's approach). In contrast, the quest to simplify is inherent in the early models of Quandt and Baumol. (43) They used Lancaster's innovations to develop a theoretical model of transportation demand which is formulated in terms of abstract mode types.


rather than the conventional car/public transport/walking trichotomy. The characteristics of each mode are expressed in terms of speed, cost, frequency of service, comfort, etc., and recognition is made of the relative importance of these attributes for different modal usage. The demand and choice of mode on a particular route depends on the absolute performance of the best mode (determining demand) and the relationship of other modes to the best mode (determining modal split). The initial model was rather naive, taking the form

\[ T_{ijm} = a_1 X_{ij} (C_{ijm}^r)^{a_2} (C_{ij}^b)^{a_3} (H_{ijm}^r)^{a_4} (H_{ij}^b)^{a_5} \]  

Eq. 1.36

where: 
- \( X_{ij} \) represents the exogenous economic and demographic variables; 
- \( C_{ijm}^r \) is the cost of travel of the \( m^{th} \) mode relative to the best mode; 
- \( C_{ij}^b \) is the cost of the best mode; 
- \( H_{ijm}^r \) is the journey time by the \( m^{th} \) mode relative to the best mode; 
- \( H_{ij}^b \) is the journey time by the best mode.

Calibration of this model was via multivariate regression. In fact, the model is similar to the unconstrained gravity model in that changes in the supply side affect both trip distribution and modal split as well as the total number of trips made over the entire transport system.

The initial formulation proved very inadequate when tested against Californian data; comparisons between the abstract multi-mode and a single mode model found the latter to be decidedly
superior. The poor results stem partly from the shortcomings of the simple model, some of which have since been rectified, and partly from computational and theoretical difficulties which appear insurmountable without some loss of accuracy.

Early criticisms by Gronau and Alcaly concerning the modal choice aspect of the model point to discontinuities in preferences with, for example, changes in the attributes of 'intermediate' modes having no effect on modal selection but the introduction of, say, a faster mode affecting choice regardless of its cost. Substantial work has subsequently been done on this specific problem and some others closely allied to it. Quandt himself devised a modified structure which solved the problem of additional modes increasing total travel but not affecting the demand for existing modes. A great deal of work has been done by Mayberry who has developed a theoretical basis for modal selection making use of a two-stage argument. He argues initially that total travel from i to j is determined by:

$$T_{ij} = A_i A_j g(L_{ij1}, \ldots, L_{ijm})$$

Eq. 1.37

where $T_{ij}$, $A_i$, $A_j$ are as before and $g(\ldots)$ is some function of modal attributes. Modal split is then determined in accord with:

$$T_{ijm} = \left[ \frac{f(L_{ijm})}{\sum_m f(L_{ijm})} \right] T_{ij}$$

Eq. 1.38

where $f(\ldots)$ is some function dependent upon the characteristics


of a single mode. If the attractiveness of the $m$th mode increases, then the demand for it will rise at the expense of the other modes and in this situation Mayberry demonstrates that the possible forms taken by $f(\ldots)$ and $g(\ldots)$ are very limited.

Similarly, work by Quandt and Young\textsuperscript{48} has circumvented some of the problems exposed by the California study where it was found that income elasticities estimated by the basic model tend to conceal considerable differences in the income elasticities among the users of different modes (especially the motor car). Their introduction of 'dummy variables' for the income elasticities associated with the different modes and routes, however, tends to be a move away from the concept of the 'abstract' mode.

Calibration of a number of alternative formulations using Californian and Northeast Corridor data\textsuperscript{49} seem to suggest the existence of significant differences in income elasticities among the city pairs (values ranging from one to three) which appears to require still further modifications if a satisfactory explanation is to be forthcoming. A similar problem which may need additional dummy variable stratification is discussed by Bergsman\textsuperscript{50} who argues that price elasticities may be higher for commodities than for people, at least above some 'cut-off' price level, which suggests a possible demand curve for the transport of a good, as shown in Figure 1.4.


\textsuperscript{49} Ibid., pp. 203-214.

Figure 1.4

$L_{ijm}^r$ is the cost of transport between zones $i$ and $j$ by mode $m$ relative to other modes.

Recent advances in the statistical field have enabled the development of more sophisticated models. The initial model, in its log-linear form, implies a multiplicative specification of the error term which would result from a full stochastic model of the form:

$$v = ax^b e^u$$  \hspace{1cm} Eq. 1.39

where $u$ and $v$ are jointly normally distributed error terms. Until recently, it has not been possible to calibrate equations of this specification; however, work by Goldfeld and Quandt (51) has resolved the problems of obtaining maximum likelihood estimates in these circumstances. Similarly, the use of 'generalised least

squares' has enabled allowances to be made for any intrinsic qualities which may be associated with particular city-pairs; this circumvents any difficulty caused by a joint error term composed of both a random element and a component that is an intrinsic characteristic of the $i_j$th arc.\(^{(52)}\)

Perhaps the most interesting advances in abstract mode theory have come from Anthony Blackburn who has set travel demand in the context of a demand function consistent with the theory of consumer's choice and, at the micro level, has introduced differences in tastes and income.\(^{(53)}\) This moves away from the early Quandt/Baumol studies where attention was focussed primarily on 'goodness of fit' criterion. Blackburn postulates differences among the individual travellers in their underlying utility functions and income levels and, hence, their responses to the service characteristics of the various modes. He introduces a number of parameters to represent the underlying behavioural differences among potential travellers with respect to the performance characteristics of the modes. A multivariate probability distribution is assumed over the parameter space and is employed to estimate the expected number of travellers likely to use each mode (i.e. market demand at each set of prices and service characteristics across modes).

\(^{52}\) Quandt and Young, op. cit.

Another approach offering hope for the future is the pooling of time series and cross-sectional information within the context of an abstract mode model. This would overcome the criticisms levelled against the conventional time series study where attention is directed entirely at a single mode. The objection to the single mode analysis is that it simply provides estimates of direct demand elasticities and neglects cross-elasticities which, on the whole, tend to be larger. This, although of only minor importance when the mode analysed has only a small share of the total market, becomes increasingly important as the mode's market share rises.

A model using the two types of data has, in fact, been constructed using CAB data. The naive Quandt/Baumol model was transformed with the introduction of terms to explain increases in travel demand not related to specific modes (disposable income per capita, etc.) and by the exclusion of the gravity term. The initial model failed to provide a reasonable fit and yielded a number of illogical signs for the elasticity co-efficients.

As a modification, the model was adapted so that the attributes of the various modes were measured relative to a single 'base' mode. The logic behind this comes from the idea that consumer choice is less likely to be based on a set of best characteristics not realised by any of the available alternatives than on comparisons of each mode to one of the existing modes (for the purpose of the model, any mode may be used as the base since all the relevant attributes will be represented). This reformation behaved better.

than the initial model but still proved inferior to the naive Quandt/Baumol specification. The probable cause of this latter result is that multicollinearity appears greater in the pooled data than in the simple cross-section; a difficulty which may only be circumvented by the application of cumbersome non-linear procedures.

The availability of more appropriate data and the development of more sophisticated techniques would not solve all of the problems presented by the model outlined above. A major drawback is that if there is a change in the characteristics of any mode, this will only alter the demand for that mode and the base mode. In order that the effects of such changes are reflected in the demands for all of the available modes, it is necessary for all demand relations to be functions of all attributes of all the modes rather than to simply employ a base mode as a surrogate for all of the others. This criticism is specific to the model above and it may be possible to overcome it by specifying a simultaneous set of relationships where the demand for all modes is estimated simultaneously. (55)

Whereas much of the earlier work on abstract modes concentrated on aggregate models dealing with the travel patterns of the inhabitants of geographical zones within the study area, more recent emphasis has been on a disaggregated approach treating the individual as the basic behavioural unit rather than the zone (e.g. the work of Stopher and Meyburg (56)). This approach circumvents the


statistical problems associated with aggregation and, theoretically more important, enables the planner to assess the effects of policy variables on travellers. The problem at the moment is to extend the disaggregate approach to choices other than between modes and to devise some satisfactory system of aggregation which would enable forecasts to be made for groups of people rather than just individuals.

Theoretical improvements of the types discussed above are only gained at the expense of considerable computational complexity; indeed, as Blackburn said of his own work, "Whether or not these advantages [of a firmer theoretical base] offset the severe difficulties surrounding its estimation and refinement is for the reader to decide". (57) Remaining with his model, we see that his non-linear function requires an iterative procedure to minimise the sum of squares which will increase in its complexity as the number of definite integrals increase. Similarly, advances using pooled data are only possible if the empirical evidence is available for solution of the models. The future of the abstract mode approach seems, therefore, to depend on the extent to which more efficient numerical means can be devised for solving non-linear functions defined over many definite integrals and upon the future availability of better inter-city passenger travel data.

1.4 Conclusions

Although the concept of explicit demand models has an intellectual appeal, in practice the creation of a workable model has eluded the analyst. In addition to the academic systems discussed above, there have been various other attempts at applying direct economic theories "in the field" (58), but to date results have shown wide divergences in the parameters obtained; a consequence partly resulting from the assumptions employed. The multivariate forms these models have taken stems from the complex nature of the problem under consideration for, although conceptually straightforward in purely abstract terms, the increased demands for realism, coupled with the necessity to include large numbers of alternative modes, routes and characteristics, can only lead to bigger and more involved structures.

A rather more important consideration is the fact that to date no satisfactory method has been devised to ensure that the predictions supplied by explicit models fall within the bounds of what is thought intuitively possible. The sequential approach does, at least, allow the planner to adjust his predictions at each of the various sub-modelling stages if they appear too unreasonable but no such "safety valve" is incorporated in the explicit model. There is no way at present, despite the claims of Quandt, Baumol and others (59), of ensuring that predictions will fall within the


59. e.g. "The abstract mode approach will then play a role not only in estimating the future demand for each mode, but also estimating the total demand for travel", Quandt and Baumol, op. cit., p.26.
bounds of reason unless, as suggested by Wilson, an independently determined trip generation rate is employed as a constraint. The basic difficulty with direct estimation is that any discrepancy in the basic model tends to magnify with aggregation; a feature of the relationship:

\[ T_i = \sum_j \sum_m \sum_p T_{ijmp} \]  

Eq.1.40

There is thus justifiable cause to continue work on aggregate travel demand models not simply to improve the reliability of the existing forecasting sequence but also to act as a constraint in the direct economic demand models. The trip generation model must, however, allow for movements along the aggregate demand curve for travel and not simply assume shifts in the demand schedule due to changes in income, tastes, etc., without any variation in the costs of travel. We now turn to consider the 'generation' sub-model in more detail.
2.1 Trip Generation

The trip generation stage of the transportation planning process determines the scale of the ultimate changes that are recommended. Although there is now a growing interest in trip generation techniques, in the past research has tended to concentrate on the 'more complex' problems of assignment, distribution and modal split. The complexities of these sub-models may have a certain appeal to the academic mind but in practical terms the emphasis is illogical. The size of the traffic forecast determines the level of aggregate expenditure, hence it seems sensible to investigate the factors influencing trip generation especially as any proposal involving a major modification to the transportation system is comparable in magnitude to decisions made by large companies on investment policy. It is even more illogical when one considers the sensitivity of the forecasts to the quality and type of data used in trip generation analysis.

The use of the term 'generation' can lead to a certain amount of confusion. It is sometimes used in a particular sense to describe the new components of the traffic stream which have been encouraged to travel by improvements in the transportation system (i.e. 'generated traffic'); this might more usefully be designated 'induced traffic'. Traditionally, in the transport modelling context, trip generation was used as "A general term which can be
applied to any part of the traffic created by one or more land uses.\(^1\) and was seen as "synonymous with the flow too and from an area of land".\(^2\) This type of definition follows the ideas of the 'Traffic Science' approach, which emphasises land-use characteristics as the determinants of trip generation. More recently, the trend has been to treat travel as dependent upon a much wider range of variables, giving explicit recognition to the relationship between travel behaviour and the social and economic, as well as the physical, state of the urban environment.\(^3\) Such an approach removes the sole reliance upon land-usage and rightly suggests we examine the complete urban environment.

The early importance attached to land-usage is, however, understandable; it was a convenient way of studying trip generation because it embodied tangible, stable and predictable quantities which are also measurable. However, this does not compensate for the shortcomings of using such a limited empirical base. The problem is that people make trips and they tend to be influenced by a multiplicity of factors in addition to land-usage. Mayer and Smock\(^4\) provide a firm empirical background for this line of argument by demonstrating that the same land-use may be observed to be compatible with widely differing trip generation rates within the study area at the same point in time. For this reason, forecasting

2. W.R. Blunden: - Introduction to traffic science No.3; Land use activities, Traffic Engineering and Control; Vol.9, 1967, pp.732-736.
now focuses on people and households rather than geographical areas. The tendency is to look at income, car-ownership and other personal characteristics and the role of land-usage has become that of a control; useful in checking rates and determining where people are likely to relocate. Hence, we can say that the trend, initiated in particular by the pioneering work of Oi and Shuldiner, is towards an analysis based upon the socio-economic characteristics of the household (or zone) rather than of the geographical area itself.

2.2 Economic Implications of Trip Generation Theory

Turning, for the moment, from the general discussion of definition and the development of the current best practice approach, it is perhaps worthwhile to look at basic economic theory underlying trip generation analysis.

For simplicity and purposes of exposition, we begin by considering the case of a low density urban area. In such circumstances, general knowledge of the comparative advantages of the various transport modes would suggest that there would be a tendency for the population to favour the private car for personal travel. The nature of the urban environment is such that there are few constraints on motor travel; ample road space enabling rapid movement. These conditions mean that there will be little feedback from traffic conditions to the rate of trip generation.

and hence the latter may be considered in the light of factors external to the transport system, e.g. employment rates, population densities, income levels, etc. In these circumstances, a zonal generation model would relate the number of trips made any particular zone \( y \) to the measurable characteristics of that zone \( x_1, x_2, \ldots, x_m \) in the form:

\[
y = a + \sum_{i=1}^{m} b_i x_i
\]

Eq. 2.1

The parameters \( b_1, b_2, \ldots, b_m \) being determined in a multivariate regression analysis employing cross-sectional data. Forecasting then involves predicting the values of \( x_1', x_2', \ldots, x_m' \) for the target year (we denote such values as \( x_1', x_2', \ldots, x_m' \)) and feeding these into the equation to give future estimates of trips generated \( y' \) where:

\[
y' = a + \sum_{i=1}^{m} b_i x_i'
\]

Eq. 2.2

This simple model implicitly assumes shifts in the aggregate demand curve for trip-making and employs no price or cost variable. The assumption of a near perfectly elastic supply curve for road space is justification for this approach. As we see in Figure 2.1, it removes any necessity for considering movements along a demand schedule, the only movements are along the supply curve. Even under these assumptions, however, the analysis is by necessity rather limited in its longer term applications. It implicitly assumes that the underlying cost/trip generating function is invariate with time; in other words, shifts in the demand schedule are of a parallel nature. If, however, the cost/trip generation relationship
changes over time, then an additional cost of trip-making variable must be incorporated in the model even under assumptions of a perfectly elastic supply of road space. If this is not done and the cost/trip generation relationship becomes less elastic over time, then overestimates of generation rates will be forecast.

![Figure 2.1](image)

The analysis can now be extended to deal with longer, and usually older, urban concentrations where limited road space considerably reduces the advantage of the car. In these circumstances, it is to be expected that public transport will have an important role to play, especially in carrying commuters. Automobile traffic will now be influenced by the supply of road space and the economic and other controls placed upon it. The amount of travel undertaken will no longer be determined simply by shifts in demand against an horizontal supply curve, but will involve a new equilibrium being established with a change in the generalised cost of travel. In other words, over time there will be movements along the demand schedule, as motorists adjust to a
positively sloped supply curve, as well as shifts in demand due to changes in the socio-economic characteristics of the population.

Looking at demand for travel first, the normal economic assumption that demand is a function of price, other things being equal, is adopted; we then denote the operating cost per vehicle-mile as $c$, the volume of traffic (per vehicle-mile) as $m$ and the tax levied per vehicle-mile as $t$, giving a demand curve:

$$m = f(c + t)$$

Eq. 2.3

Logically, the next step is to calibrate the parameters of this curve but there is no simple way of doing this. The tendency in transportation planning is to implicitly incorporate the demand curve in the various sub-models which form the planning process. Even if such a curve can be constructed for current conditions, the difficulties of forecasting future variations may be insurmountable.

Generally, the supply of transport facilities is defined as:

$$c = g(m/x)$$

Eq. 2.4

where $c$ indicates the cost of operating a vehicle as a function of the level of traffic per unit of road space. It is usual practice to treat this as depending upon two important relationships; namely, the speed-flow relationship and the operating cost-speed relationship. Present estimates of the supply curve are fairly easy to derive and reasonable assumptions can be made about future conditions which may affect it.

The actual level of traffic \( (m) \) is then estimated by solving the above equations specifying the demand and supply curves; in doing this \( m \) and \( c \) are treated as unknowns. The objective of the planner is to minimise the total operating costs by manipulating the supply curve (which is influenced by the design of the transport plan) and/or shifting the demand curve (which may be varied if the transport plan alters land-usage patterns or the socio-economic characteristics of the population).

The model set out above\(^7\) is crude in the extreme, but it does outline the basic Marshallian economic theory underlying the study of trip generation. It paints, however, a rather idealistic picture of traffic forecasting and does not really provide a firm practical basis to prediction. We now move on to the more practical aspects of the problem, looking initially at the major influences affecting travel generation and then progress to a detailed analysis of the statistical techniques which suggest themselves applicable to this type of study.

2.3 The Variables of Trip Generation

The ultimate purposes of trip-making form a useful basis upon which to classify trip types. Here, we will adopt the simple delineation suggested by Oi and Shuldiner\(^8\) and differentiate

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between 'Consumption-orientated' and 'Production-orientated' travel. The former concerns trips in connection with leisure activities, while the latter includes those trips which are necessary to enable a living to be earned. Obviously, some journeys evade such classification but these are small in number and can be safely ignored.

From the above, we can see that the demand for trip-making is 'derived'; that is, it is not desired for its own sake but because it enables the demand for other commodities to be satisfied. Oi and Shuldiner(9) talk of 'joint demand' for trips in combination with the associated final activity, but this can lead to confusion. The consumer wants to reach a particular destination and the accompanying trip is simply a means of achieving this ambition. It seems unrealistic to say that the consumer wants to both reach his goal and travel or that travel enhances the benefits which are derived from the final activity. Indeed, it seems probable that in most cases there is only disutility associated with travel.

The terminology adopted by Oi and Shuldiner results from the desire to emphasise the importance of considering travel in association with final activities. We accept the objective but not the specific terminology.

Conventional neo-classical economic theory suggests a number of factors which influence the demand for consumer goods:

9. Ibid., p.12.
"The list of factors influencing the household's demand may conveniently be summarised.... that demand (i.e. the amount of a commodity the household is prepared to purchase) is a function of (i.e. depends upon) the price of the good in question, the prices of all other goods, the household's income and its tastes." (10)

As the demand for travel is derived from the activities which travel permits, we must add to these the influence of the prices of these final activities. We now consider these various factors in greater detail.

Initially, we look at what is often referred to as the 'catch-all variable' in economic theory, namely the tastes of consumers. Generally, this is a difficult variable to quantify and in practice econometric travel models include proxies to measure its influence, e.g. age, race, sex, marital status, employment, etc. More recently, the trend has been towards combining these surrogate variables into 'social-status' indices. It is certainly true that various social classes (if such stratification can be legitimately undertaken) have different patterns of final demand and so it is assumed their trip-making behaviour varies correspondingly. Taste, however, tends to be correlated with other variables, notably with income, making it difficult to isolate its particular impact.

The occupation of the head of the household is a prime determinant of the living standards of a family and hence acts as

an indicator of the social status of the family. P.W. Shuldiner\(^{(11)}\) claims that although it exerts a minimal positive effect, this probably results from close association with family size and vehicle ownership. However, Walker\(^{(12)}\) feels this under emphasises the importance of the variable and supports his argument with observations taken from the Chicago Area Transportation and the Puget Sound Regional Transportation Studies. Recognising the problems of multi-collinearity, he controlled all factors other than the occupation of the head of the household (i.e. family size, car-ownership and residential density). He concluded that the occupation of the head of household is influential at any moment in time but data inadequacies prevented him testing the relationship over time. He argues that the role of this variable is likely to be of greatest significance when analysing particular areas of a city because each category of occupation he defined tended to monopolise their 'own' urban area.

Type of dwelling unit reflects differences in consumption patterns, although we again meet the problem that this variable is correlated with many others, especially income and distance from the Central Business District (C.B.D.). The usual argument is that the more permanent the type of dwelling unit (an owner occupied house rather than hotel room), the more a family is likely to be integrated into the local community and the greater its trip generation rate. Support for this is found in the fact that the


permanent dwelling unit is generally capable of providing the
greatest garaging space facilitating high car-ownership rates.
Oi and Shuldiner (13) suggest that there may be a counter effect to
this in as much as temporary accommodation is not conducive to
lengthy stays and so may have a positive effect on trip generation.
Shuldiner's empirical evidence shows, as we might expect, a high
correlation between dwelling unit type and family size and income
but after allowing for this he finds that "average trip frequencies
increase with increasing degrees of permanency"; (14) a relationship
found to be statistically significant but small.

A further variable which we might include under taste is
household size and structure, as Shuldiner says, "If travel is a
function of human activity a relationship should exist between the
frequency of trips made from the home and the size of the family
making such trips". (15) It is obviously true that the more people
there are in a family, the more trips are likely to be made but to
postulate an exact relationship requires more than this. The size
of the family exerts two influences: firstly, personal trips will
tend to increase in proportion with family size but, secondly, the
number of trips of a communal nature increase less than proportionately.
Consequently, we expect travel demands to increase at a slower rate
than the increase in household size. Shuldiner, (16) using data
from the Modesto (California) O-D survey, found that average trip

13. Oi and Shuldiner, op. cit., pp.120-123.
15. Ibid., p.41.
16. Ibid., p.45.
frequency rises at a rate of 0.8 trips per day for each additional person in the family. However, this tends to level off once there are four people or more in a dwelling unit. It is not just size but also the family structure which is influential; generally, adult members make more trips than do minors, employed people more than unemployed and males more than females. Obviously, there are problems in untangling such factors but in London there is evidence that the number of workers per household and the number of students per household are significant. (17)

Many of the factors influencing consumer taste have been combined to form social-economic indices. One such index was devised in the U.S.A. by E. Shevky and W. Bell. (18) Strictly, they defined three indices classifying according to: (a) Social Rank - based upon educational levels and worker type, (b) Degree of Urbanisation - based upon fertility rates, participation of women in the labour force and the incidence of single family dwelling units and (c) Extent of Segregation - based upon the proportion of each area’s residents belonging to specified minority groups. Shuldiner (19) included these indices in his analysis of the C.A.T.S. data and found that, although car-ownership was the main independent variable, the urbanisation index exhibited a very high negative correlation with trip frequency. The low urbanisation index was thought to reflect greater attachment to the home as measured by larger proportions of children, fewer women in the labour force, and

larger fractions of single family dwelling units. Families who choose to reside in low urbanisation zones exhibited a preference for a way of life centring around the home. The shortcomings of the Shevky-Bell indices is their use of zonal averages in compilation; this, as we see later, can lead to misleading results in regression analysis.

A considerable amount of empirical work concerned with consumer demand patterns has found that income is one of the important determining variables. This extends to the examination of consumption-orientated demands for trip-making. Economic theory indicates that, with the exception of 'inferior goods', a rise in the real income level leads to higher consumption, leading to an expectation of a positive correlation between the level of family income and its trip-making rate. Further, high income families are capable of affording the costs of some of the more 'luxurious' activities which additional travel can provide; this tends to reinforce the positive influence discussed above. Empirical evidence bears out the importance of income levels in the study of trip generation, e.g. the London survey found that: households earning over £3,000 averaged 9.5 journeys daily, almost three times the rate (3.3) observed in households below £500 income; and similar findings appear in the bulk of other surveys.

Micro-economic theory also tells us that the quantity of a good demanded varies inversely with its price. The derived nature of...


the demand curve for travel means that its price elasticity will
also be influenced by (a) the price of the journey relative to the
combined price of the final activity plus associated travel, and
(b) whether there are close substitutes for the travel-related
leisure activities. Although extensive work has been carried out
looking at the price of travel, especially the evaluation of
tavel time, the complications mentioned above (section 2.2) have
made the inclusion of an explicit price variable in the generation
model difficult. From observations, it has been found that, other
things being equal, people living near centres of congested cities
spend less of their budget on travel than those living in suburbs.
This is thought to reflect differences in the costs of trip-making,
consequently either distance from the C.B.D. or residential density
are often as use of indicators of the responsiveness of aggregate
travel demand to varying price situations. The influences of these
variables tend to be multifarious however. The distance from the
C.B.D. does not simply indicate the price of travel, but also
reflects higher income levels as one moves into the suburbs. This
income effect may offset the price effect as we move further from
the city centre. In addition, it has been argued(22) that
distance from the C.B.D. is merely a "space parameter" and,
especially if the centre itself has been changing in character, as
such is a weak and unreliable determinant for forecasting purposes.

We now turn to production-orientated travel. Here we are
only concerned with the travel necessary to get to and from the

22. N. Cherniack: - Critique of home-interview type O-D surveys in
urban areas, Highway Research Board Bulletin, No.253, 1960,
p.168.
place of work and not with any travel which is actually associated with the job itself. The most obvious variable to be included here is the number of employed persons in the household. A worker makes a fairly constant number of daily trips in order to pursue his occupation (usually two, but seldom more than four), especially in relation to the social/recreational travel of families as a whole, which can differ widely. We can find empirical support for this: firstly, from F.H. Wynn, who found that in twenty modern American cities, "Work trip volume is more constantly related to city size than is the over-all volume of internal travel generated by urban populations" (23) (where city size may be taken as a good proxy for employment) and, secondly, in a study of Ponteland (Northumberland), T.E.H. Williams et al. found that work journeys form an increasingly large proportion of total household travel as the size of the family declined (24) while the number of social/recreation trips decreased, hence showing the constancy of work travel rates per family but increasing consumption-orientated travel as the number of unemployed members rise. (This is not to say that work trips are totally unrelated to family size, obviously they are, but rather that the relationship is not proportional.)

If data is of a more aggregated nature, an examination of employment levels rather than employed persons per household, may be required. As employment is itself dependent upon the level of demand for the commodity being produced, it will fluctuate with the


demand for the final good. Because it is almost impossible to allow for this, forecasters generally adopt the equilibrium assumption of full employment. This simplifies matters considerably as the number of factors needing consideration is reduced to two: population size and labour force participation rates. The former poses few problems. Participation rates depend upon the age, sex, marital and racial composition of the population; information which can usually be obtained from census data.\(^{(25)}\)

The two other variables usually associated with production-orientated trips are their price and income. It is frequently argued that journeys to and from work cost little in relation to the wage earned and hence price is not considered a significant influence on the number of trips made, but this is too simple. A worker has a number of alternatives open to him, depending upon the price of available substitutes: he can (a) reduce his work travel by, say, taking lunch at his place of work, but the scope for such substitution is limited; (b) can walk or cycle to work rather than pay for motorised transport, or (c) change his place of employment or the location of his home so that his travel costs are reduced. The fact that lower-paid workers tend to minimise their production-orientated travel costs by either walking or cycling to their work (which is not usually registered as a journey in O-D surveys) combined with the historical concentration of cheaper housing in close proximity to high employment areas, goes a long way to explaining why F.H. Wynn found a significant correlation between work trips and income levels.\(^{(26)}\)

\(^{(25)}\) For further details, see Oi and Shuldiner, op. cit., p.16.

\(^{(26)}\) F.W. Wynn (1959), op. cit., p.22.
This exhausts the list of variables likely to be major influences on the demand side of our equation, but before turning to consider the supply conditions a few general comments are required. Economists attempt to produce simplified models of market situations but when quantifying the relationships the need to resort to proxies in the place of many of the suggested variables often results in the inclusion of factors which influence both supply and demand. The dual role of these proxies means that several of the variables discussed below have already been encountered when demand was being considered. Further to this, it is almost impossible to make neat divisions between those variables affecting supply when looking at urban travel (e.g. a higher demand for car trips can lead to changes in the supply conditions via the level of traffic congestion).

The most obvious variable to consider when discussing the supply of transport is the level of car-ownership. This is usually found to exert a strong positive influence over the trip generation rates and has been favoured by forecasters because of its apparently straightforward nature (although there are problems of cross-correlation with other included variables). Ownership of a car provides a family with a flexible mode in which to satisfy their existing travel demands and also supplies the means to undertake new journeys. Additional trips resulting from the availability of a car may actually cost more than they would have done if public transport had been used (an alternative which had in the past been ignored) but because the traveller only considers his perceived costs (e.g. petrol and perhaps oil) and ignores costs not directly related
to usage, there is an illusionary economy. In addition, each car added to a family's stock tends to increase the number of trips that family makes, but it will do so at a diminishing rate. These fairly obvious statements are supported in empirical work. We have already noted Shuldiner's findings on the subject and these are substantiated in the London Traffic Survey, the Ponteland Survey and the CORSS project; to name but a few.

L.A. Thompson and C.H. Madden go a little further for, when they were looking at rural travel in Virginia, they found that, "Vehicle ownership is directly related to travel, the more cars a family has and the newer they are the more the family travels." (28)

Two important criticisms have been raised against the use of car-ownership levels as a predictive variable: one empirical and the other theoretical. Sharp, Hansen and Hamner, using data from the Washington surveys of 1948 and 1955, found that the relationship between vehicle ownership and trip generation was not stable over time. An analysis of the same data, however, by W.L. Mertz and L.B. Hamner goes some way to explain the apparent unreliability of this relationship. When 1948 data is fed into the basic equations, it is found that the level of trip-making in 1955 is overstated, but they add, "This was primarily due to a change in procedure as to what constitutes a dwelling unit; the more recent study accounts for a greater number of dwelling units, such as


rooming-houses, military installations, and so forth, than did the earlier study.\(^{(30)}\)

The second criticism is not so easily dealt with. Oi and Shuldiner, with justification, feel that car-ownership is not an exogenous variable but is determined simultaneously with the trip generation rate.\(^{(31)}\) They suggest that larger models should be constructed so that the mutual dependence is treated with the respect that it deserves. Although this is probably the correct theoretical approach, it raises two practical problems: firstly, the basic transportation model is built upon cross-sectional data collected from O-D surveys, whereas much of our knowledge on factors influencing car-ownership rates comes from time series analysis. Secondly, some of the more recent research on car-ownership tends to indicate that it may not be so closely related to the conventional variables of trip generation work as Oi and Shuldiner suggest. In a very up-to-date study of car-ownership in The Netherlands, G.G.J. Bos found that:

"The tests used clearly show that both income and price do not contribute in any way to the increase in the total number of cars.\(^{(32)}\)"

He found that a simple logistic trend offered the best predictions. Despite these two arguments, further study of the inter-relationship between trip generation and car-ownership would be worthwhile.

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31. Oi and Shuldiner, op. cit., p.87.
Obviously, not all journeys can be made by private cars and in order to explain the others we need to look at the supply of public transport facilities. Here, we are dealing with a qualitative rather than a quantitative variable and hence, although attempts have been made to devise a 'public transport index', the tendency is to use proxies such as distance from the C.B.D. and/or residential density. The assumption here being that public transport facilities decline with both distance from the C.B.D. and declining residential density. This would indicate that trip-making by public transport falls in the suburbs but this was not found to be significantly so by Oi and Shuldiner when data from the Modesto Traffic Survey was considered. Similarly, it would be thought that travel would decline, other things being equal, with falling residential density if the argument above holds, but again Oi and Shuldiner, this time using data from Chicago and Detroit, find that "careful analysis fails to isolate density as a significant variable when the effects of vehicle ownership and family size are taken into consideration." (35)

Some recent studies have adopted a rather more general approach when considering the supply of transportation facilities by looking at the quality of service offered by the transportation network as a whole. In earlier work, network characteristics were introduced at a later stage in the planning process but now it is thought that the restraints imposed by the network will not only affect the

34. Oi and Shuldiner, op. cit., p.98.
35: Ibid., p.100.
distribution of trips but will also ultimately reduce trip generation (see Chapter 1). The use of socio-economic variables only to explain trip generation is therefore inadequate. The impact of network quality may, however, be felt indirectly on trip generation inasmuch as network quality may be correlated with the socio-economic determinants (e.g. it is reasonable to link the quality of the network with the level of car-ownership) but it is also possible when no such link exists for changes in the quality of service offered by the network to vary whilst the socio-economic variables remain unaffected with the result that no change is forecast in the trip generation rate. Furthermore, the quality of network service can be expected to vary within the urban area at one point in time depending upon the utilisation and capacity of the various parts of the network. This can then be expected to influence trip generation rates in different parts of the area. To develop a forecasting model based upon network quality variations between areas, one needs to be able to identify the relevant variables causing the variations in quality. This leads us to the concept of 'accessibility'.

An attempt to allow for differences in network quality was made in Phase II of the London Traffic Survey, where generations per zone were made dependent upon zonal variations in public transport services as measured by bus and rail 'accessibility indices'.(36) These indices were based upon the frequency of service to the zone relative to the size of the zone. Zones were then categorised as 'high', 'medium' or 'low', depending upon the value of the index.

Such an index has the limitation of excluding the private transport network which is probably a more important influence on trip generation - a fact the G.L.C. openly admits, "There is no dispute that a car affords a household a different order of accessibility and trip-making rates reflect this strongly."(37)

Phase III of the London Transportation Study attempted a rather more practical approach to the problem; here, "The main technical problem was to produce a traffic model that in some way related trip generation to transport capacity and in which assignments were sensitive to congestion."(38) The method employed used category analysis to determine the basic level of trip generation and then a linear programming technique (involving a series of iterations) was used to relate link capacity with travel demand. The objective was to maximise the number of attractions subject to the link capacity of the system, i.e. the final assignments must give loads which do not exceed the assumed capacity of each link. The technique was to allow successive speed reductions at the assignment stage on the overloaded links "with the objective of obtaining an equal overload condition."(39) Those trips which could not be accommodated were either considered not to have been made or were diverted to public transport. The problem is that speed reductions do not reduce the demand itself; some overloading may still occur. In reality, the shortage of capacity will limit trip generation and

39. Ibid., p.9.
regulatory measures, such as parking controls, may also be introduced to manage the demand. In practice, however, it proved impossible to synthesise this process and instead trip generation rates were lowered arbitrarily in car-owning households regardless of the intensities of demand for different trips and consequently ignoring their relative sensitivity to regulatory measures and congestion. This technique may have certain practical advantages but its shortcomings emphasise the need to develop a generalised generation model which will allow for network quality and regulations on parking, etc.

This concludes the discussion of the variables usually found in trip generation studies. No attempt has been made to compare the claims of each variable for inclusion in the generation model but rather the a priori arguments for suspecting some relationship between each of the variables and the generation rate have been stated and a limited number of empirical studies which either support or reject the theoretical propositions have been cited. Now, we turn to look at the techniques employed to decide which variables offer the best explanation of the generation rates and to the methods of specifying such relationships for forecasting purposes.

2.4 Some Statistical Problems

In this section, we examine the various mathematical and statistical techniques which have been utilised in trip generation forecasting. The model finally adopted must not just give a good
statistical fit to current data but must also take a logical and meaningful form. It is fairly easy to obtain good fits for the current situation but is much more difficult to produce reliable relationships for prediction purposes. This means that the included variables must not only be meaningful determinants of current trip-making patterns (so that significant changes in their magnitude are reflected in realistic changes in the generation rate) but they must also be predictable to enable estimates of future trip generation to be derived. The early studies relied upon the desire line plot (which was a simple graphical presentation of airline distance between origin and destination with the volume of travel indicated by the thickness of the lines) but this was too general to be of any real use, giving only a picture of past and/or present conditions. As a result, multivariate regression techniques (40) have been widely adopted and today all trip generation forecasting is based upon this powerful technique or some modification of it.

Any attempt at forecasting is going to be subject to some degree of error. There are three basic types; namely, (a) errors in estimating the independent variables, (b) errors in the simulation of the dependent variables and (c) errors in the forecasting equation using the independent variables. To select the 'best' trip generation procedure, the objective becomes one of minimising this joint error.

40. For details of regression procedures, their theoretical limitation and underlying assumptions, see H. Theil:- *Principles of Econometrics* (North-Holland), 1971.
In regression analysis, we are concerned with choosing an estimate so that the sum of the squares of the deviations of the data from the estimate is a minimum. As regression analysis is concerned with squares of deviations, it seems appropriate to express the composite error as

\[
\text{Joint Error} = \sqrt{\text{error}^2_{\text{in estimation of independent variables}} + \text{error}^2_{\text{in estimation of equation to simulate dependent variables}} + \text{error}^2_{\text{in predictive power of equation over time}}}
\]

These possible sources of error are considered in turn:

(a) **Errors in the Estimation of Independent Variables**

The data used in generation studies is usually collected in household surveys and supplemented by information made available from the census. The former obviously suffers from the normal defects of a voluntary sample, especially from poor response rates. There is also the problem of fitting census data, which may only be updated every quinquennium, into a system which is primarily based upon data gathered at a particular point in time. These are, however, problems encountered in most fields of forecasting and it is questionable whether more extensive sampling would justify the expenditure of greater sums of money involved in gathering detailed information.

In general, a well conducted survey will keep the errors in the determination of the current values of the variables small in relation to the other types of error, and the nature of transportation studies provides a series of checks to correct any discrepancies, e.g. screen-line counts can be used to check the generation rates obtained from
From a statistical point of view, if it is possible to calculate the ratio of error variance (i.e., the errors in both the independent and dependent variable), then it may be possible to overcome the problems of poor measurement by modifying the regression method (e.g., use either orthogonal or diagonal regression). The alternative may be to use instrumental variables, although, in practice, these are difficult to find and in any case there is always an element of arbitrariness in their selection.

The main work concerning itself with the problems of errors in variables is that of Deutschman, although even here they are not treated in isolation but combined with errors in the equation simulating present conditions. For data, he used the information made available by the household survey conducted by the Tri-State Transportation Commission which studies travel patterns in 22 counties which encompass the New York City metropolitan area. He assumed various levels of error in the independent variables (income, density and vehicle ownership), this error being a constant percentage of the actual zonal value, its sign (plus or minus) being generated by random number index. He then determined the joint error of reproducing the survey and estimating the independent variables in a single calculation by running a regression analysis with fixed errors in the independent variables. By studying the standard errors, he was able to see which combinations of variables

41. Details of the various surveying techniques are found in M.J. Brutton: "Introduction to Transportation Planning," 2nd Edition (Hutchinson), 1975.


formed the most suitable equation given certain percentage errors of measurement. His conclusions prove to be rather limited:

"This joint error incurred in estimating the independent variables and reproducing the survey data (for the dependent variables) does not itself yield a single clear-cut choice of trip generation equation (or procedure). It does narrow the list of variables and equations, however, to a few which now must undergo the test of forecasting efficiency."(44)

(b) Errors in Estimation Equation to Simulate Dependent Variables

In the past, many travel forecasts have been based on zonal data which is understandable since the output of the trip generation model in the transportation planning process is generally in the form of forecasts of trip-making for defined geographical areas: the 'traffic analysis zones' or 'districts'. This has created two controversies: firstly, what is the best method of conducting a regression analysis based upon zones, and, secondly, is this approach to be recommended in any case?

The main problem using zonal least-squares techniques is to decide whether to express the variables in terms of mean values per zone (e.g. trips per household per zone) or in aggregate totals (trips per zone). Intuitively, one would think that both methods would produce similar results - especially as they both involve the same degree of aggregation and because total trips per zone is simply the mean trips per household per zone multiplied through by the number of households in the zones. In their work using data obtained from the Tri-State Transportation Commission, Kassoff and

44. Ibid., p.44.
Deutschman found that "the aggregated total equation has a slight statistical advantage but the rate equation offers more flexibility and efficiency in analysing the data, because it is not tied to the data scheme to which it was developed". (45) Support for these conclusions is to be found in the Perth Case Study. (46)

Douglas and Lewis (47) argue that there is no real choice open to the forecaster. The only difference between the two approaches lies in the inherent assumptions made regarding the distribution of their respective disturbance terms. A basic assumption of least-squares is that the error variance of the disturbance terms is constant, i.e. there is homoskedasticity. In fact, as the disturbance terms resulting from the use of mean values for the zones is simply the disturbance terms of the aggregate totals divided by the number of households in the zone, this condition cannot be satisfied in both cases unless the number of households in each zone is constant (or allowance is made for heteroskedasticity by applying suitable multipliers to each equation. They then proceed to argue in favour of using rate variables because all aggregate variables reflect zone size and hence their residual errors will tend to be related to this. However, due to their susceptibility to sampling error and mis-specification, the rate variables will not guarantee a constant error variance although

46. Perth Case Study Report, Vol.VIII.
it is more likely to satisfy this condition than the aggregate variables. These arguments explain why the Cardiff Development and Transportation Study\(^{(48)}\) obtained remarkably high multiple-correlation coefficients by using aggregate variables and condemn Bruton's rather hasty conclusion that "the high correlation coefficients achieved in the analysis show quite clearly that a strong relationship between land-use and trip generation".\(^{(49)}\)

The advisability of using zonal data can now be considered. The underlying assumption of this areal aggregation is that contiguous households exhibit some similarity in family or travel characteristics and this, accepting what we have said above, allows them to be grouped or aggregated using mean parameter values for each group. The statistical implication of this is that the difference between the zonal mean values are more expressive of the spacial distribution of the parameters than are the extremes to be found within a zone; i.e. it is assumed that the zones are homogeneous. In reality, such uniformity within zones is seldom, if ever, encountered due to the vast diversity of land-usage within any geographical area. Furthermore, even if such uniformity can be assumed at any moment in time, it is unlikely that it will hold through time, thus zoning also creates problems in forecasting.

The problem is most easily seen in mathematical terms. If the data is expressed in terms of summed squared deviations about

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49. M.J. Bruton, *op. cit.*
the mean, then the total sum of squares (T.S.S.) is:

$$\sum_{j=1}^{K} \sum_{i=1}^{n_j} (X_{ij} - \bar{X})^2$$  \hspace{1cm} \text{Eq. 2.5}

where: $X_{ij}$ is the $i^{th}$ observation of variable $X$ taken in zone $j$;

$\bar{X}$ is the grand mean of variable $X$, i.e. $\frac{\sum_{j=1}^{K} \sum_{i=1}^{n_j} X_{ij}}{N}$;

$N$ is the total number of observations and $n_j$ is the number of observations in zone $j$;

and $K$ is the number of zones.

Because the data is grouped, we can split the total sum of squares into the sum of squared deviations within each zone and the sum of squared deviations between zones, i.e.:

$$\sum_{j=1}^{K} n_j (\bar{X}_j - \bar{X})^2 + \sum_{j=1}^{K} \sum_{i=1}^{n_j} (X_{ij} - \bar{X}_j)^2$$  \hspace{1cm} \text{Eq. 2.6}

where: $\bar{X}_j$ is the mean value of $X$ in zone $j$.

The problem now becomes one of quantifying the relative importance of these two components. Using data from the Madison Transportation Area Transportation Study, Fleet and Robertson found that their results indicate that, by far, the greatest proportion of the total variation is within areal units and is lost, in so far as its usefulness to trip generation analysis is concerned. (50)

Furthermore, the increased aggregation which has been adopted by many studies to improve the fit of the regression does not overcome the problem but rather aggravates it; the statistical improvement is meaningless in the face of a varying base. The use of smaller zones may reduce the within zone variance relative to that between zones, but this can lead to a further problem by increasing the

errors in variables (a result of the zonal mean having to be calculated on a smaller sample) which will lead to biased estimates. In any case, the empirical evidence submitted by Fleet and Robertson (51) demonstrates that in all probability even small zones will exhibit the greatest proportion of total trips variability within, rather than between, the zones. (52)

In addition to this, Gerald McCarthy argues that the use of zonal means implies the assumption of normality to the distribution of the variables in each zone; otherwise, the mean would not be the appropriate measure of central tendency. To see if such an assumption is justified, he examines evidence made available from a survey conducted in Raleigh, North Carolina, and after inspecting the distributions of particular variables within selected zones, he concludes that the "data indicates that the zonal averages for household automobile ownership and family size deviate to some degree from the central location of the zonal data, this providing a basis for questioning the validity of the assumption of the representativeness of the zonal average". (53)

51. Ibid., p.16.

52. An empirical investigation of the effects of zonal aggregation on the values of $R^2$ in regression models is presented in Appendix 1, albeit in the context of car ownership, rather than trip generation, modelling.

Some researchers (54) argue that a study of trip generation should ideally concentrate on individuals' behaviour patterns, not the household. In his doctoral thesis, Vickerman, for example, argues that the individual is "the primary decision-making unit" (55) and proceeds to study non-work trip-making magnitudes in this context. The difficulty with this line of argument is that it ignores travel undertaken by members of the household for collective reasons. In other words, it ignores the interaction between the members of the household. The problem becomes clearer when we remember that a household or family has a given monetary budget which acts as an effective constraint on the trip-making decisions of each individual member of the household; a trip made by one member of the family often prevents another from travelling. The difficulty also occurs over the availability of the family car to each licence holder in the household. A rather more practical reason for looking at individuals is advanced by Burrell in support of his 'hybrid curvilinear model' (56); his argument rests upon the assumption that there are fewer types of persons than types of household. The fallacy of this becomes apparent in Hodges' work, where over two thousand categories of person are required to calibrate


his generation model successfully. (57) Individual-based models have a certain novelty value but practically the requirement to specify intra-family relationships in sufficient detail to determine their effect on travel behaviour seems too complicated for the advantages obtained.

The arguments set out above have led to the widespread acceptance of household generation models (in the U.S. at any rate); however, before leaving this particular point a few closing comments are needed. To begin with, it has been observed that the conventional statistical indicators (i.e. the coefficient of multiple determination) suggest that the estimates derived from aggregation are preferable to those obtained from household data. Kassoff and Deutschman, for example, explain 71.4% of the variation in trip-making when using zonal aggregates compared with an explanation of 30.9% when using household data. (58) This greater accuracy is deceptive. In fact, the coefficients obtained are not comparable as they refer to different types of variation. The $R^2$ of the household-based equation indicates that some 30.9% of the total variation in travel rates is being explained whilst the coefficient from the zonal equation indicates that 71.4% of the variation between the zones is being explained but this forms only part of the total variation.

Moving on to the implications of aggregation for forecasting, we find that the reliability of zonal equations decreases over time.

57. E.D.T. Hodges, op. cit.
58. H. Kassoff and H.D. Deutschman, op. cit., p.27.
(i.e. heterogeneity and skewness vary over time). The necessary condition for relationships developed from areal data to retain their reliability for forecasting purposes is that the "ratio of the within-zone-variance to between-zone-variance, with respect to all variables, is expected to remain constant over time".\(^{(59)}\) In the short-term, it may be argued that there will be little change within the zones and hence their predictive power may be quite strong over a period of, say, up to 20 years (as suggested by Harwood and Miller).\(^{(60)}\) There is tentative empirical evidence to support this based upon a study of Phoenix, Arizona. Using data collected in 1956-7, Brady and Betz used a zonal regression model to predict the generation rate in 1964 and, after distributing through a gravity model, found that their results compared favourably with details of actual trip-making as indicated by screenlines set up in the target year. They concluded, "Certainly .... the relationship between trip generation and socio-economic characteristics can be quantified and does remain relatively stable over time".\(^{(61)}\) As E. Judge pointed out, however, comparisons made between screenline counts and trip generation predictions by zones are of questionable validity.\(^{(62)}\)

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We now turn to another type of error encountered when applying econometric procedures, namely the problems created by cross-correlation between the explanatory variables. We have already noticed, when listing the factors influencing generation rates, that not all of the independent variables are in fact totally independent and this results in parameters which are very sensitive to errors in the data. It is obvious from this that the existence of multi-collinearity reduces the predictive powers of any equation system. There are, however, a number of techniques available which can eliminate or at least reduce the effects of cross-correlation. Often the condition is pinpointed by large standard errors of the regression coefficients but this was shown to be unreliable as far back as 1936. An alternative is to use confluence analysis (or its graphical counterpart: 'bunch map analysis') but this has not been so successful as initially hoped.

The method most commonly employed in trip generation analysis is 'category analysis' (or 'cross-classification' or 'rank classification'). This technique has gained in favour recently as it has the further advantage that it may be used with reasonable success utilising only census data. The pioneering work in this field was undertaken in the Puget Sound Regional Transportation Study (P.S.R.T.S.) where zonal category analysis was used.


More recently, household techniques have been developed, especially by Wootton and Pick. (66) One of the classical advantages of this modification is that it may be possible to develop a predictive technique applicable universally and, indeed, results to date are promising. (67)

The idea is to construct a multi-dimensional matrix in which each dimension represents one independent variable. In addition, each independent variable is stratified into a number of discrete class intervals. The objective is then to determine the average response or value of the dependent variable for each of the defined 'categories' of the independent variables. For forecasting purposes, it is then necessary to assume that these 'average responses' remain stable through time; making forecasting a matter of predicting how many households fall into each category at the target year and multiplying these by the average number of trips made by households falling in the respective cells.

The approach used by Wootton and Pick was to allocate households to some 108 categories defined as combinations of three variables: family income (six structure groups), car-ownership (three groups).


67. For example, one commentator reports, "A comparison of generation rates for the West Midlands and London has been made and shows remarkable similarity, particularly when the differences in public transport facilities are considered in the two areas .... further work in the West Midlands where trip rates gained from the urban study area have been applied to rural areas in North Worcestershire and produced trips which have checked well against measured traffic flows", N. Borg:- Transportation studies: a review of results to date from typical areas, No.2, West Midlands Conurbation, Institute of Civil Engineering, 1968, p.18.
and family structure (six groups). The S.T.E.P. programme developed by these two then proceeds to associate 18 mode and purpose combinations with the 108 cells. In Phase III of the London Transportation Study, use was made of 81 categories comprising three income groups, three car-ownership groups, three residential density groups and three levels of employed residents per household, and these are calculated for three journey purposes.

To forecast individual cell values from the aggregate changes in the variables, a distribution is associated with each variate. Wootton and Pick find that they can represent the distribution of households by income using a Gamma function,\(^{(68)}\) and for the family structure they hypothesise a Poisson distribution for family size and a Binomial distribution for the number employed. They estimate the number of households falling into each car-ownership cell by initially allocating households to income classes and from these the level of car-ownership for each is determined from a Gamma-based probability function. These distributions are chosen for fit and analytical convenience but they may be questioned, e.g. the lognormal distribution may be more appropriate for distributing income.\(^{(69)}\)

\(^{68}\) The gamma distribution take the general form

\[ P(x; \theta, \lambda) = \lambda^\theta x^{\theta-1} e^{-\lambda x} / \Gamma(\theta) \]

where \( P \) is the probability function of a variable \( x \) given parameters \( \theta \) and \( \lambda \). It is of particular use in forecasting income because \( \lambda \) can be interpreted as a scale factor and \( \theta \) as a spread factor enabling both growth and distributional considerations to be incorporated. A rather more detailed look at the properties of this distribution is to be found in J.J. Bates: Some notes on gamma distributions, M.A.U. Note 213, 1971.

Although category analysis has certain advantages, it is not without its critics. It is sometimes argued that its appetite for data is excessive, especially if the underlying distributions are highly skewed. It has been estimated by Douglas and Lewis that some 250-500 households need to be sampled in each important category (especially those likely to be prevalent in the forecast years) to establish mean trip rates with any degree of confidence. (70) Advocates of the technique are not so pessimistic and it has been argued that, "In practice, the majority of trips come from a fairly limited segment of the total possible categories and the accuracy or otherwise of the extremes is unimportant." (71)

Perhaps a more damning criticism is that it is difficult to test the statistical significance of explanatory variables thought to be relevant in the trip-making decision. They have to be considered exogenously, although graphical techniques may assist in this process. There are other methods available (e.g. sign tests, differences between means, differences between medians and chi-square contingency table designs) but their strength is limited. The most promising approach appears to be the incorporation of the categories, as dummy variables, in a normal regression model and then to use conventional methods to test their statistical significants.

Two further, but less important, disadvantages of rank classification are that: firstly, that it only makes limited use of


data compared with the more powerful multivariate regression techniques. By forming all variables into discrete categories, a considerable amount of information is lost and the naturally continuous nature of many distorted. Secondly, there are practical problems involved if new variables are to be incorporated into the model as this requires the recalculation of the entire category matrix due to the complex nature of the inter-relationships between the household variables.

The respective advantages of category analysis and least-squares can be combined by introducing dummy or dichotomous variables into the regression equations. (72) When a regression, suitably specified, of \(Y\) on all dummy variables is run, the least-squares coefficients of the dummy variables are simply the cell means; in other words, multiple regression based entirely on dummy explanatory variables is identical to category analysis. In this form, all dummy variable regression suffers from the same defects and advantages as category analysis. This is only one specific dummy variable specification, however, and it is possible to combine such variables with continuous variates to produce the benefits of both forecasting techniques. For example, normally least-squares makes hard work of curvilinear responses (requiring transformations of the variables) and discontinuities in the independent variables; the introduction of dummy variables circumvents these difficulties, although it has the limitation that one implicitly assumes that it

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is appropriate to use dummy variables rather than running a series of regression, one each for the attributes separated by the dichotomous variables. If this assumption is not valid, then it is perhaps preferable to categories by the discrete variables and then run a regression for each based on the continuous variables. (73)

Before moving on to errors in forecasting, mention must be made of a further statistical technique for overcoming the limitations imposed by multi-collinearity. This is principal components analysis, which isolates those principle factors which dominate the behaviour of economic variables. This is done by describing the independent variables as a linear function of a number of other hypothetical variables. Although this technique offers a number of advantages, no use of it has been made in generation work; this is probably because "the economic interpretation of principal components in general is no easy matter". (74) An alternative is factor analysis: a technique originally developed by psychologists to test hypothesis about the organisation of mental ability. The objective is to isolate a limited number of factors which 'explain' the matrix of covariances; centroid analysis being used for this purpose. (75) In a sense, we can say that principal component analysis

73. A detailed discussion of the relationship between multivariate regression analysis and category analysis is presented in Appendix 2, which also looks at the advantages of a hybrid model marrying the two techniques.


75. A strict definition of factor analysis is that it is "a formal model about hypothetical variables which account for the linear relationships that exist between observed variables", S.M. Mulaik: The Foundations of Factor Analysis (McGraw-Hill), 1972, p.96. A case for using multivariate analysis of this kind in studying trip-making behaviour is made out by F.P.G.M. La Fors: - Statistical aspects of trip generation models, Colloquim Vervoersplanologish Speurwerk, 1974.
is a special case of factor analysis, being variance orientated rather than co-variance orientated.

A trip generation study using factor analysis has already been undertaken by S.T. Wong using zonal data from the Chicago Area Transportation Study. Being dissatisfied with the limited explanation of travel offered by Oi and Shuldiner, using the same data he took some 28 variables and applied factor analysis "to determine what underlying patterns are associated with trip generation among the 28 variables and 57 analysis zones in Chicago". *76*  

Seven factors were obtained (general size; modal choice; social status; general trip purpose; school; ride and personal business). Interpretation of these yielded a number of surrogates (average car-ownership; % of trips made by persons 5 years old or over; % of trips by car driver and passenger; % of trips per 1,000 square feet of floor area; % of personal trips to work and % of personal trips to eat a meal) which were then employed in a multiple regression.

Wong's study is open to a number of criticisms. Although he seems able to relate his factors back to the original variables with little difficulty, many of his variables, and in consequence some of the surrogates he selects, are descriptive in nature not 'causal'. It is difficult, for example, to see how the modal split variables (included in the surrogates we have the percentage of trips by a car driver plus a passenger) are causal. A second criticism is that the use of zonal data means his factors, taken

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together, do not account for 81.5% of the total common variance as he claims but only 81.5% of the common variance between zones. A further point is that he appears to have decided to adopt factor analysis because he had no clear theory and hence arrived at his choice of variables after the factor analysis rather than making use of the technique as a hypothesis testing device. A more appropriate method is to formulate some hypothesis and to test it using multivariate analysis. Certainly further work using these techniques on either a household or personal basis is required to overcome problems of multi-collinearity.

(c) Errors in Predictive Power of Equation Over Time

Finally, we turn to the third type of error: errors in the predictive power of the equation over time. We have discussed some of the components of such errors, e.g. multi-collinearity and zonal regression, but the most important is perhaps the use of cross-sectional data in predictive models. This is a practical limitation imposed by the need to obtain data from O-D surveys which can only provide cross-sectional descriptions of urban travel at specific points in time. Use of such data assumes "it is possible to specify explicitly the difference among the economic units in such a way that once the characteristics are specified, the economic units will, on the average, react in the same manner to any particular stimulus". (77) This assumption is unlikely to be fulfilled as cross-sectional analysis necessarily excludes certain dynamic factors and hence overstate the influence of the

included variables. This tends to make cross-sectional relationships approximate to long-run relationships, whilst the time series relations reflect short-term relations. Recently there has been a tendency to try and obtain time series data in transportation studies and this might help to throw some light on the stability of the calculated parameters through time. Meanwhile, it is perhaps advisable to adopt Kuh's suggestion that "the estimated coefficients be used with the greatest circumspection in their application to time series processes". (78)

2.5 Conclusions

It has been shown that economic theory can supply a basic framework upon which trip generation models can be built and that statistical techniques are available for calibrating the relevant parameters. Future work in the field could fruitfully be directed towards the application of rather more sophisticated statistical techniques to the trip generation stage of the transportation planning process, especially to the problem of determining the appropriate variables for consideration. This may involve the use of more complex least-squares systems when it is necessary to determine certain equations simultaneously and the use of other branches of statistics, especially multivariate theory, to overcome some of the inherent shortcomings of regression models in this type of situation. The longer term reliability of parameters may


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be improved with the introduction of pooled regression techniques which can combine the information obtained from a number of cross-sectional household surveys gathered through time. The future lies in this direction because any improvement in data collection is likely to be slow; restricted by the financial and physical limitations on the adoption of more comprehensive sampling methods. Thus, the tendency is probably going to be towards better analysis rather than better information.
CHAPTER 3

AN ECONOMIC CRITIQUE OF CAR OWNERSHIP FORECASTING MODELS (1)

3.1 Approaches to Car Ownership Forecasting

This chapter is concerned with offering an economic critique of the techniques currently employed in car ownership modelling and forecasting. It looks especially at the validity of the underlying theory and the theoretical justification for adapting specific model forms. Little attention is paid to the variables employed – this is left to the following chapters which have a much higher empirical content. The aim of the chapter is to separate out the most useful modelling procedures although it soon becomes clear that all have their inherent weaknesses and strengths.

Over the past forty years many attempts have been made to predict car ownership. These predictions have been used for a variety of purposes, and in consequence a number of quite distinct approaches to car ownership forecasting have emerged. Car manufacturers, oil companies, and suppliers of sundry complementary

products want information concerning both the potential total market for their goods, and the variations which are likely to sell well (e.g. car size). This is basically market research and we shall refer to such investigations as 'market' studies. In contrast, the information sought by the government is concerned primarily with the absolute number of vehicles likely to be seeking road space, regardless of their individual peculiarities. We shall refer to forecasts of national vehicle ownership, divided into only a small number of categories, as 'aggregate' studies. A third type of forecasting is undertaken for much smaller areas to estimate the demands likely to be made on local road systems. Such forecasts usually form only part of a more comprehensive transportation planning process which involves all modes of transport. We shall refer to such studies as 'spatial'.

Market forecasts are usually for a much closer time horizon than is common in either of the other two categories and, in addition, tend to rely almost exclusively on market surveys for their data—seeking the maximum possible information concerning consumer tastes and requirements. The car manufacturer is in the position of being able to mould people's tastes to some extent to match his own ends, i.e. he can use advertising to persuade people that they really do want a white car or whatever. The enormous economies of scale apparent in the industry and the length of time it takes to develop a new model provide strong incentives for encouraging sales of a standardised product. A result of this is that much recent analysis of the consumer market undertaken by manufacturers has concerned toleration of a model rather than trying to find exactly what is wanted.
Aggregate forecasting is basically concerned merely with forecasting the number of vehicles on the road at some particular date. This usually involves some calculation of a trend in ownership rates which are then extended into the future. To the extent that these predictions are merely accepted by governments and used as a basis for policy decisions on the expenditure of public funds on goods which complement the utility derived from car ownership (e.g. roads, bridges, parking facilities) they are to some extent self-fulfilling. However, the government could use the predictions to guide their policies towards controlling car sales via credit restrictions and indirect taxation. Some aggregate studies forecast sales of new cars, and these are of interest to the manufacturers, as well as the government. On the other side of the coin, the government is now becoming much more closely involved with manufacturers, even to the extent of discussing the likely prospects for individual models.

A unique feature of spatial forecasting is the use made of cross-sectional data obtained from household surveys in the study area. As we shall see later, it has proved difficult to introduce economic variables into aggregate forecasts from time series data, since these variables are often correlated with each other over time. Hence, although the forecasting equation purports to allow for changes in the explanatory variables, this will only be so if they keep in the

same relation to each other as in the estimation period. Cross-
section data has facilitated the development of 'behavioural' econo-
metric models which attempt to explain car ownership, or car purchase
in terms of individual or household characteristics.

Before passing on to look at the various methods used to fore-
cast car ownership, it will be instructive to look at how such fore-
casts fit into the transport planning process, both at the aggregate
and spatial level. Generally, in standard transportation planning
models, the level of car ownership is assumed to affect the number of
trips made, and the modal split of these trips. However, in the
real world these will not be determined in sequence, but simultaneously.
This was pointed out in the early 1960s by Oi and Shuldiner (3) who
argued:

"Logical considerations suggest that car ownership and
trip generation rates should be mutually determined in
some larger model - that is the solution to some system
of simultaneous equations taking account of the joint
demands for automobiles and trips. The treatment of
car ownership as a predetermined explanatory variable
appears to be a pragmatic device, imposed by the
available data and our ignorance of urban travel
behaviour"

and as restated more recently by Vickerman (4):

"This is a question of some interest: whether car
ownership per se affects trip rates causally, or
whether it is primarily the underlying socio-economic
factors which influence car ownership and hence trip
rates, or, more fundamentally, whether the socio-
economic factors influence the potential trip rates,
which then induce car ownership".

3. W.Y. Oi and P.W. Shuldiner: An Analysis of Urban Travel Demand
(Northern University Press), 1962.

Indeed, if the current methods of aggregate trip and car ownership analysis are accepted, then for forecasting purposes the car ownership model is effectively redundant. Suppose we have the following household-based trip generation and car ownership regression equations:

\[ T_i = b_{10} + b_{11}P_{Di} + b_{12}C_i + b_{13}Y_i + b_{14}S_i + e_i \]  
\[ C_i = b_{20} + b_{21}P_{Di} + b_{22}Y_i + b_{23}S_i + u_i \]

where \( T_i \) is trips generated by household \( i \), \( PD \) is residential density, \( C \) is car ownership per household, \( Y \) is income, and \( S \) is a social index of some form. This can be rewritten in reduced form as a single trip generation equation:

\[ T_i = (b_{11} + b_{12}b_{21})P_{Di} + (b_{13} + b_{14}b_{23})Y_i \]
\[ + (b_{21} + b_{22}b_{23})S_i + v_i \]

In practical terms this would considerably simplify the current procedure. It removes the need to forecast car ownership explicitly. Unfortunately, however, it lacks any consideration of feedback effects. For example, additional trips will add to congestion and this may affect the stability of the parameters of the car ownership equation. It appears, therefore, that a separate car ownership forecast will continue to be of value, even in spatially disaggregated models.

3.2 Extrapolation Procedures - Theory

The fitting of a trend to car ownership growth was first attempted to obtain national (aggregate) forecasts, but the ready availability of local registration data soon led to its use in
spatial studies. Clearly car ownership cannot be assumed to keep growing at the present rate, since once most potential licence holders have a car the potential for further growth is greatly reduced. Hence 'S' shaped (called 'sigmoid') functions are fitted to the time series observations. The sigmoid curve has generally been approximated by either a lognormal or logistic curve.

Early work on fitting such curves to car ownership data was done by de Wolff (5) and Roos and van Szeliski. (6) In 1949 Duesenberry (7) propounded the economic theory (following the idea of a product life-cycle) that underlies such curves in terms of a diffusion process by which new products at first sell slowly, because of high production costs and technical problems on the supply side and because of uncertainty, ignorance and unfamiliarity on the demand side, then very quickly, if the product is to be successful, economies of large scale production enable prices to fall while a 'Veblenesque' effect develops to stimulate demand in a band-wagon fashion as consumers become more orientated towards the new product, and then more slowly as the market becomes saturated with per capita ownership levels reaching a plateau. By making strict assumptions about utility functions he found that, with a bell-shaped income distribution, the growth path of a new commodity "would not be unlike that of a logistic curve".


6. C.F. Roos and V. van Szeliski:- Factors governing changes in domestic automobile demand, in the Dynamics of Automobile Demand (General Motors Corporation), 1939.

7. J.S. Duesenberry:- Income, Saving and the Theory of Consumer Expenditure (Harvard University Press), 1949. The author felt his theory applied to all consumer durables and not exclusively to cars.
The logistic curve was first used in biometrics and a critique from this area, of the commonly used growth models, has been written by von Bertalanffy. In this comparative study he looked at the decaying exponential, the parabola, the Gompertz curve, the exponential and the logistic curve and came to the conclusion that:

"None of these expressions is apt to reproduce the essential and basic characteristics of the usually observed curves of growth. It is important to note that this criticism is not based upon the consideration that some particular sets of growth data are not well fitted by a certain formula. Rather, it has been shown that none of these formulas is concordant with the trend and characteristics generally found in empirical growth curves."

Returning to car ownership, several writers, notably Farrell and Cramer suggested that the cumulative log-normal distribution was superior to the logistic. More recently the logistic curve has again found favour. In the United Kingdom the forecasts used by the Department of the Environment are based on the methods developed by Tanner at the Transport and Road Research Laboratory. The basic method is to fit a logistic curve, and then make adjustments to allow for various assumptions about the growth in income per head, and in the 'cost of motoring'. Because of the importance of this method for official forecasts in Britain and elsewhere we shall describe it in detail.


Tanner supports (12) his use of the logistic curve as follows:

"It seems reasonable to suppose that as well as being smooth the growth curve should continue the curve of growth experienced in the immediate past. This means that in 1960 the forecast curve should take the actual value and that the percentage rate of growth per year should be close to that experienced in the few years up to 1960.

The Algebraic form of the forecast curve is largely open to choice. It must have at least three constants that can be fitted, for if there were only two the whole curve would be determined by the current number of vehicles per head and its rate of growth... A type of curve often used to represent growth, in both social and biological phenomena, is the logistic curve... It has three constants and tends upwards toward a limit with the passage of time. The percentage rate of growth decreases steadily as the upper limit is approached...

To find the third constant required to determine the forecast curve, it is necessary to estimate the upper limit, i.e. the maximum number of vehicles per head that will ever be demanded."

A logistic curve can be fitted, then, if we know the following three parameters: \( C_0 \), car ownership per person at time (year) \( t = 0 \); \( g_0 \), the rate of growth of \( C \) at year zero (i.e. \( \frac{dC}{dt} \), evaluated at \( t = 0 \)); and lastly \( S \), the saturation level to which \( C \) is asymptotic as \( t \) increases. It is a property of the logistic curve that the rate of change of the variable in question (here \( C \)) is proportional to the product of the level the variable has reached at that time and the distance it is away from the saturation level. Thus for our case (13) we have:

12. Ibid., p.264.

13. The following is abstracted from J.C. Tanner: Forecasts of vehicles and traffic in Great Britain, Transport and Road Research Laboratory Report, LR 650, 1974.
\[
\frac{dC}{dt} = aC_t(S - C_t)
\]

Eq. 3.4

where \(a\) is a constant.

The solution (14) to the differential equation 3.4 is

\[
C_t = \frac{S}{1 + be^{-aSt}}
\]

Eq. 3.5

where \(b\) is a constant of integration. At time zero we have:

(i) from 3.4  \(g_o = a(S - C_o)\) 

Eq. 3.6

(ii) from 3.5  \(C_o = \frac{S}{1 + b}\)  

Eq. 3.7

Hence we can replace \(a\) and \(b\) in 3.5 as follows:

\[
C_t = \frac{S}{1 + \left(\frac{S-C_o}{C_o}\right)e^{-g_oSt/(S-C_o)}}
\]

Eq. 3.8

Thus, if we know \(C_o\) and \(g_o\) for some year, and if we can also estimate \(S\), we can read off from 3.8 the car ownership per person at any year \(t\). Normally we cannot hope to 'know' \(S\), and so we must estimate it. Figures 3.1 and 3.2 illustrate graphically the method normally used to fit logistic curves to car ownership data.

14. To check this differentiate equation 3.5 with respect to time, gives

\[
\frac{dC_t}{dt} = \frac{(1 + be^{-aSt}) \frac{dS}{dt} - S(-asbe^{-aSt})}{(1 + be^{-aSt})^2}
\]

\[
= \frac{as^2be^{-aSt}}{(1+be^{-aSt})^2}
\]

since \(\frac{dS}{dt} = 0\)

\[
= \frac{aeC_tbe^{-aSt}}{(1+be^{-aSt})^2}
\]

from Eq. 3.5

\[
= \frac{aeC_t(S - C_t)}{(1+be^{-aSt})}
\]

from Eq. 3.5 again
The procedure consists of two stages. Firstly $S$ is estimated by regressing the growth in cars per capita itself. The saturation level is given by the intersection of this (extrapolated) regression line with the cars per capita axis. In algebraic terms we derive estimates $(\hat{\alpha}, \hat{\beta})$ for the coefficients of the regression equation.
\[ g = \alpha + \beta C - \varepsilon \quad \text{Eq. 3.9} \]

and put \( g = 0 \) to give the (saturation) level of \( C \) at which growth stops:

\[ S = \frac{-\alpha}{\beta} \quad \text{Eq. 3.10} \]

Since we would expect \( \beta \) to be less than zero, and \( \alpha \) to be positive, \( S \) is also positive. The 't' subscripts are not included in equation 3.9 since the regression may be estimated using either cross-section or time series data.

Once we know \( S \) we can use equation 3.8 to derive the growth path of car ownership. Tanner, (15) however, in his later forecasts allows for variations in the approach path towards this fixed saturation level by letting 'a' vary with income per capita and motoring costs. Equation 3.8 then becomes

\[ C_t = \frac{S}{1 + \left( \frac{S-C_0}{C_0} \right) Y_t^{k_1} C_0^{k_2} P_t^{k_3} P_0^{k_4}} \quad \text{Eq. 3.11} \]

where \( Y_t \) is income per head (fixed prices), \( P_t \) is 'cost of motoring' (fixed prices), and \( k_0, k_1, k_2 \) are constants. It should be noted that equation 3.11 is only one way that these variables could be used to effect car ownership, although Tanner argues that it is the most consistent with the overall logistic specification. This type of modelling, which represents a movement away from the extrapolative approach, is considered in more detail in section 3.5-4.

3.3 Extrapolation Procedures: Practice and Objections

One objection to the logistic curve technique is that it assumes that the saturation level is fixed and remains constant over time. However, studies conducted at different points in time have tended to produce higher and higher saturation levels as the years have passed. Burrell (16) argues that such shifts are the result of the differing attitudes towards car ownership of the different generations within society. He argues that later generations are more "car orientated" and will therefore have higher saturation levels. In terms of Figure 3.1 we would expect the line to move to the right (over time) for cross-sectional data, and to bend upwards at the lower part of the previous line for time series data. These effects are illustrated in Figures 3.3(a) and 3.3(b), where C is the car ownership level, and g is its percentage rate of growth. This may provide the reason for the shifts in the saturation level but it hardly provides practical assistance to the forecaster who is left with the task of trying to separate a trend resulting from familiarisation with a product from the life cycle effects which accompany the age distribution of the population.

Perhaps the strongest critics of the logistic curve technique have been Beesley and Kain. (17) They are particularly suspicious of the use made of the method in "Traffic in Towns" (18) where, they

18. Despite these reservations this report dominated much of official thinking on urban transport policy for the next decade.
argue, the forecasts employed depend initially on extrapolations of the 1950-60 figures but thereafter (for the next 15-20 years) increasingly reflect the saturation level estimate. They argue that the selection of 0.40 as the appropriate saturation level is based entirely on U.K. cross-sectional data for the period 1956-60 and that supplementary information, both from alternative time periods in the United Kingdom and contemporary statistics in the United States, is ignored because it yields substantially different results. Tanner, in a subsequent defence of his technique, (19) does not answer these points directly but, rather, attempts to elaborate on his concept of saturation and explain why the saturation level may vary. He contends that "there is a level of ownership which no increase in income or decrease in price will cause to be exceeded", and although

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this saturation level may vary with circumstances it is unlikely to decrease through time.

In fact we can isolate three possible definitions (and hence measures) of saturation:\textsuperscript{(20)}

(1) A ceiling level of a car ownership variable which it is not possible for a group of people to exceed. The saturation level is seen as being a binding constraint on the maximum per capita level of ownership, independent of the level of income, motoring costs and other such economic variables. It may be thought of as the 'income no object saturation level'.

(2) The saturation level may merely be a statistical parameter of a sigmoid growth curve never intended to approach its upper asymptote during the period under review. When forecasting future car ownership it may be argued that primary attention should be paid to fitting recent data adequately rather than to arranging the growth curve to pass through some preordained point in, say, 30 years' time. The 'saturation level' in this context should be regarded just as one more parameter to be extricated, and not of any consequence in its own right.

(3) Saturation may be seen as an 'average' long-term level of car ownership variable predicted by the model as the independent variables follow their predicted or hypothesised courses over time. Since real income will be predicted to grow exponentially this appears similar to the first definition.

but two differences exist - (a) while real income grows exponentially other variables may be held more or less constant hence, because this affects the distribution of ownership, the saturation level is likely to fall below that of the first definition, (b) changes in official policies may limit the eventual saturation level of car ownership; the first definition implicitly assumes there is only one set of policies (normally those currently in force).

Tanner's whole emphasis is on the first definition although the quotation cited suggests he is cognisant of the distinction between this and the third definition.

A major point of contention between the logistic curve school of thought and the views expressed by Beesley and Kain is the latter's argument that car ownership should be closely related to income in the traditional economic fashion. In supporting their ideas Beesley and Kain develop a regression model using income and residential density as independent variables and study the effect on future ownership rates of varying the growth paths of the explanatory variables. The multiplicity of results obtained (each dependent upon the assumptions employed) tend, however, only to add to Tanner's argument that it is almost as difficult to forecast future income levels as it is to forecast car ownership growth. Tanner's \(^{21}\) comment in 1966 adequately sums up the position reached midway through the 1960s: "I do not think that there are any absolute criteria for choosing between these

\(^{21}\) Tanner (1966), op. cit., p.145.
two approaches. Both are in some sense reasonable methods, but I at present happen to have greater confidence in the one that I have used". Later, in 1974, as we have seen, Tanner allowed for various assumptions about growth of income and motoring costs to affect the rate of convergence to the saturation level, but not to affect the saturation level itself.

Adams (22) questioned the T.R.R.L. method of estimating the saturation level of car ownership on two grounds. Firstly, he questions the legitimacy of using car ownership as the independent variable for estimating the saturation level with the rate of change in car ownership as the dependent variable. He argues that if the saturation level is to be used for prediction purposes the reverse relationship is appropriate. Regressions on the latter basis produce a saturation level of 0.28 cars per head which is well below TRRL estimates (0.51 for this data, i.e. for U.K. counties 1970-72).

Figure 3.5 is drawn as a sketch of the actual situation, for illustrative purposes only, to show the difference between Tanner's g on C regression, and Adams' C on g regression. If there were a perfect relation between g and C both lines would be coincident and the problem would disappear. When predicting from regression lines we should use the g on C line if we knew C and wished to predict g,

Figure 3.5

Data range for car ownership (C) and its growth (g) together with g on C, and C on g regression lines (ILLUSTRATIVE ONLY). Cross-sectional data on Great Britain counties 1970-72

and the C on g line if we knew g and wished to predict C. Adams says we know that at saturation \( g = 0 \) and we wish to predict C, so we should use the C on g line giving us \( C = 0.28 \). However, this cannot possibly be the saturation level since once \( C = 0.28 \) the g on C line would predict \( g > 0 \) and C would continue to grow. In fact 0.28 is the answer to the question 'if the growth rate of one county were found to be zero what would be the most likely level of car ownership in that county?'.

104.
A second objection is that the data Tanner uses shows only a weak connection between \( g \) and \( C \), which will cause the results to be erratic and the saturation level estimate will be biased upwards. Tanner\(^23\) uses data from English counties for 1970-72 to obtain a saturation level of 0.51 cars per person. He then gives the standard error though as 0.10, which yields a 95% confidence interval of roughly (0.30, 0.70), which covers all sensible estimates of saturation level. Even this is not the whole story since Scottish counties have been arbitrarily excluded to improve the fit. With Scotland included (as Tanner always had previously) the saturation level point estimate is 1.72. This is the result of a nearly horizontal \( g \) on \( C \) line (see Figure 3.5) due to a low correlation between \( g \) and \( C \).

A more powerful point is that each county will be heading towards its own saturation level. These saturation levels will not be the same for all counties since, for example, population densities will continue to differ between counties, and this has been shown to be one factor having an important influence on car ownership. In the limiting situation when all counties have reached saturation the \( g \) on \( C \) regression line will be horizontal, predicting an infinite saturation level for the country as a whole. The method has broken down. Prior to this point we cannot expect the fit to be good, and this will bias the saturation level upwards.

Empirically, Adams demonstrated graphically that, for a series of sub-periods covering 1946-70, cross-section regressions produce erratic results.

\(^{23}\) Tanner (1974), op. cit.
with curves criss-crossing one another. The graph was constructed by Adams to mock Tanner's claim (24) that the cross-section regression procedure "has intuitive appeal and has been found to give consistent results".

In contrast to the cross-section approach, use of time series data can be justified even if each point is on a curve leading to a saturation level which is increasing over time. Suppose that in Figure 3.6 we observe points $X_i$ ($i = 1, 10$), each point on a curve heading for $S_i$, which is increasing over time because, say, of the increased car orientation of society, or reduced public transport facilities. The saturation level will occur when an $X$ point reaches the C axis, and this is clearly at $S_{10}$. If we only had observations

24. Ibid., p.55.
X₁ to X₅ we could have predicted this from g on C regression. Tanner estimates this saturation level as 0.34 using United Kingdom data for 1952/73. However, United States data gave a saturation level of 1.23 cars per head and so Tanner paid little attention to this method. Adams echoes Tanner's doubts about using time series data, deducing that the underlying relationship cannot be logistic.

United States data had previously been investigated by Whorf. He chose his saturation level (0.6087) by finding the logistic curve which fitted the data best (i.e. highest $R^2$). He used 1946-1972 data, whereas Tanner used 1952-1972 data, but the difference between 0.6087 and Tanner's 1.23 is startling. When testing his logistic curve against other curves, however, Whorf found that linear, quadratic, and cubic formulations all had a higher $R^2$ than the best logistic curve, which appeared to give rather a pessimistic fit. This seems to strongly indicate that the logistic curve is inappropriate. In later work, Tanner began experimenting with alternative sigmoid curves and the last T.R.R.L. update of its forecasts employing the logistic curve were the 1974 predictions which are reproduced as Table 3.1 below.


26. Taken from Table 10 in Tanner (1974), op. cit.
Table 3.1

Alternative Forecasts of Car Ownership

The 'low' forecasts assume 2% increase in real GDP, with 10% relative increase in petrol price. The 'middle' forecasts assume 3% and 2% respectively, and the 'high' forecasts 4% and 0% respectively. (27)

A saturation level of 0.45 is assumed in all the above forecasts, but Tanner notes that if the saturation level were changed to 0.35 or 0.55 the forecasts would change almost proportionately (e.g. to 17-19 or 29-31 millions of cars in 2000).

One deficiency in the T.R.R.L. forecasts, from the point of view of the transport planner, is that information is not provided

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27. i.e. petrol prices are assumed to remain at 50p. per gallon at 1973 prices.
on the number of households falling into each of the 0, 1, 2 and 2+ categories. It has been found that the ownership of a second car affects the trip generation rate of the family by something like 75% less than that of the first. Hence, over time, increases in car ownership per person can be expected to have a decreasing effect in stimulating additional trips, but this can only be accurately predicted if we have predictions by numbers of cars. Data for the recent past is presented in Table 3.2. (28)

<table>
<thead>
<tr>
<th>Year</th>
<th>0 car households</th>
<th>1 car households</th>
<th>2/2+ car households</th>
</tr>
</thead>
<tbody>
<tr>
<td>1961</td>
<td>69</td>
<td>29</td>
<td>2</td>
</tr>
<tr>
<td>1963</td>
<td>64</td>
<td>33</td>
<td>3</td>
</tr>
<tr>
<td>1965</td>
<td>59</td>
<td>36</td>
<td>5</td>
</tr>
<tr>
<td>1967</td>
<td>53</td>
<td>41</td>
<td>6</td>
</tr>
<tr>
<td>1969</td>
<td>49</td>
<td>44</td>
<td>7</td>
</tr>
<tr>
<td>1971</td>
<td>48</td>
<td>44</td>
<td>8</td>
</tr>
<tr>
<td>1973</td>
<td>46</td>
<td>45</td>
<td>9</td>
</tr>
<tr>
<td>1975</td>
<td>44</td>
<td>46</td>
<td>10</td>
</tr>
<tr>
<td>1977</td>
<td>43</td>
<td>46</td>
<td>11</td>
</tr>
<tr>
<td>1979</td>
<td>42</td>
<td>44</td>
<td>13</td>
</tr>
</tbody>
</table>

Table 3.2
Percentages of Households with Regular Use of Cars

Whorf fitted individual logistic curves to the percentage of households owning one or more, two or more, or three or more cars. Mogridge (29) follows up this work, combining it with his cross-section category technique outlined in Cheung and Mogridge. (30) This technique consists of estimating the proportion of households in each category of car ownership (i.e. 0, 1, 2, 3+ cars) by using the discrete gamma distribution. Mogridge then takes the series for the proportion of households falling in each category over time, and then fits a logistic curve to these series. This enables him to predict the percentages falling in each category in 1981.

In summary, we should note that the appropriateness of the cumulative logistic function as a simulation of the growth in car ownership through time is open to question. The logistic curve proved useful in explaining the growth of television ownership,(31) but this commodity has rapid market absorption, which is not the case for motor cars. Bonus (32) disputes this proposition, though, on evidence that car ownership in West Germany followed a logistic curve since the war as car ownership increased ten-fold. He argues

that this growth was due to economic factors rather than market diffusion. Clearly, though, if the precise impact of individual economic factors can be isolated then we would be explaining car ownership growth rather than merely describing it. This is the purpose of the econometric models discussed in the next two sections.

3.4 Econometric Models: Theory

The econometric approach to car ownership forecasting embodies an attempt to construct and calibrate statistical models which explain consumer behaviour, i.e. why should people wish to own a car? Econometric models are constructed by hypothetising the underlying causal relationships which influence car owning patterns. Statistical estimation procedures are used to find the relevant parameters, and these are then used in statistical tests of the initial hypotheses. Data inputs into these models may be either time series, cross-sectional, or, provided special care is taken, a combination of both.

The economic motives underlying a household's decision to purchase a motor car can simply be illustrated from basic utility theory. Suppose that a household's total utility (U) can be taken to be dependent upon just two variables. The first of these (Y^A) may be defined as the amount of income that remains after the fixed cost of the car ownership decision (to own or not to own) is made. The second (D) representing the sum of potential benefits to be derived by the household from visiting destinations, each with generalised cost of visiting them less than some k.
D will, therefore, be some function of k, its value rising as k increases, i.e.

\[ D = D(k, \text{---}) \quad \text{Eq. 3.12} \]

\[ \frac{\delta D}{\delta k} > 0 \quad \text{Eq. 3.13} \]

Another variable which will affect D is car ownership, C. Here more destinations will be available for given cost k if a car is owned, so \( \frac{\delta D}{\delta k} > 0 \). However, since C is not a continuous variable we should say

\[ D(k)_C > D(k)_N \quad \text{Eq. 3.14} \]

where C and N denote the car-owning and non-car-owning situations respectively.

Returning to our utility function, household utility will increase as left-over income \((Y^\Delta)\) increases, and also as more destinations become available for the given cost, i.e.

\[ U = U(Y^\Delta, D) \quad \text{Eq. 3.15} \]

\[ \frac{\delta U}{\delta Y^\Delta} > 0 \quad , \quad \frac{\delta U}{\delta D} > 0 \quad \text{Eq. 3.16} \]

The household will then buy the car if

\[ U_C > U_N \quad \text{Eq. 3.17} \]

However, the effect of car ownership on utility will work in offsetting directions through the two variables, \(Y^\Delta\) and D. This is because buying a car will reduce left-over income, such that

\[ \frac{Y^\Delta_N}{Y^\Delta_C} > 1 \quad \text{Eq. 3.18} \]

By combining inequalities 3.14 and 3.18 with 3.16 we see that a
reduced $Y^A$ works to reduce $U$, whilst the increased $D$ (due to car ownership) works to increase $U$. The familiar economic trade off situation, therefore, emerges although, since car ownership is a dichotomous 0-1 variable, it is not the 'marginal utilities to price' ratios which are equated but rather a comparison of the two utility levels, $U_C$ and $U_N$, is made.

This approach to the problem is obviously capable of considerable extension, and only a very basic version has been given above. In particular the multitude of factors affecting $D$ can be considered. Beckmann, Gustafson and Golob (33) follow this approach, using specific mathematical functions for the utilities. The resultant algebraic manipulations isolate the trade-offs between income and reduced travel time, increased accessibility and additional leisure time. Although mathematically elegant the model is hardly operational. The practical econometric models used in car ownership analysis of this type at all levels of aggregation are still very basic, and in many cases are extreme simplifications of the behaviour pattern to be explained (see Chapter 5).

Before going on to look at some of the applied work, it should be noted that many researchers have been concerned with the demand for cars as a consumer durable and, more particularly, with the demand for new cars. Here economic theory bids us to separate total demand (at time $t$) $Q_t$, into replacement demand $R_t$ (equal to the depreciation

during the period), and net investment, $I_t$.

\[ i.e. \quad Q_t = R_t + I_t \]  
\text{Eq. 3.19}

Net investment is the difference in stock, $S$, between two periods

\[ I_t = S_t - S_{t-1} \]  
\text{Eq. 3.20}

This can be made equal to some fraction between desired stock and last period stock:

\[ I_t = \lambda (S_t^* - S_{t-1}) \]  
\text{Eq. 3.21}

Replacement can be made a fraction of last period stock

\[ R_t = rS_{t-1} \]  
\text{Eq. 3.22}

We can make desired stock $S_t^*$ a function of income ($Y_t$), relative price ($P_t$), and other variables

\[ S_t^* = \alpha_0 + \alpha_1 Y_t + \alpha_2 P_t + \ldots \]  
\text{Eq. 3.23}

Hence, combining equations 3.19 to 3.23 gives

\[ Q_t = (r-\lambda)S_{t-1} + \lambda \alpha_0 + \lambda \alpha_1 Y_t + \lambda \alpha_2 P_t + \ldots \]  
\text{Eq. 3.24}

The above is a simplification of the model suggested by Stone and Rowe,\(^{34}\) although many similar models were developed independently.

Clearly, we can easily derive an equation for the total stock of cars if we wished to predict car ownership. From 3.20, using 3.19 and 3.22 we have

\[ S_t = I_t + S_{t-1} = Q_t - R_t + S_{t-1} = Q_t + (1-r)S_{t-1} \quad \text{Eq. 3.25} \]

Combining this with 3.24 gives us an estimating equation for car ownership (stock):

\[ S_t = (1-\lambda)S_{t-1} - \lambda \alpha_0 + \lambda \alpha_1 Y_t + \lambda \alpha_2 P_t + \ldots \quad \text{Eq. 3.26} \]

The standard reference for the application of the stock adjustment model to the demand for new cars is Chow.\(^{(35)}\) This basic model has, however, been modified into a state adjustment model – a more dynamic framework – by Houthakker and Taylor.\(^{(36)}\) The model is essentially pragmatic designed initially to permit medium period forecasts (up to 10 years) of consumer durable demand. It is in continuous form with

\[ \frac{dc}{dt} = Q - \delta C \quad \text{Eq. 3.27} \]

forming the depreciation assumption. This equation replaces 3.19 and 3.23 with \(\delta\) as a new parameter in place of \(r\). A direct relationship is postulated between purchases, stock and the exogenous variables (e.g. income and relative price) taking the form

\[ Q = \beta C + \gamma f(Z) \quad \text{Eq. 3.28} \]

where \(Z\) is the vector of socio-economic variables. The \(C\) variable used in this model is not only seen as a 'stock of vehicles' but also

\(^{35}\) C.G. Chow: Demand for Automobiles in the United States (North Holland), 1957.

as a psychological 'stock of habits' and, thus, is viewed as a 'state'. The parameter $\beta$ has two possible interpretations. If $\beta$ is positive, then the higher the stock the greater the purchases - suggesting habit formation. (Equation 3.27 may, therefore, be considered as reflecting purchases reinforcing habits which would otherwise wear off at a constant proportional rate.) If $\beta$ is negative, however, there is an inventory effect with the stock exerting downward pressures on purchases. The introduction of continuous time avoids complications which arise in the Stone and Rowe model (i.e. equation 3.25) if vehicles depreciate entirely within the period of observation. The combination of equations 3.27 and 3.28 yields an estimating equation of the form

$$\dot{Q} = (\beta - \delta)Q + \gamma \{f(Z) + \delta f(Z)\}$$

Eq. 3.29

In reduced form, the Stone and Rowe and Houthakker and Taylor models are indistinguishable, but the different formulations permit interpretations of one model in terms of another. This may be useful at times. If, for instance, $\tau$ in the Stone and Rowe model exceeds unity, this may be explained by the values of the components of the equivalent variable $(\beta - \delta)$ in the state adjustment model. This does, however, have the decided disadvantage that the relatively simple notion of depreciation loses its unambiguous interpretation. Habit persistence may, in some circumstances, simply become an excuse for a badly fitting model, with statistically insignificant price and income effects being explained away by overriding habit formation effects. Consequently, while the model has been successfully fitted to many consumer durables, its detailed interpretation is imprecise.
While the stock adjustment model and its extensions have dominated the empirical work on the demand for new cars for over twenty years, they do have a number of serious limitations. Empirical investigations using the model, in particular, have found that their ability to predict movements in demand is poor, mainly, it has been argued, because the effects of the standard socio-economic variables are more complex than the model allows for. It is also questionable whether the assumption of a constant depreciation rate is valid. The difficulty is that it is not the physical deterioration of the vehicle stock which is important but rather the depreciated value and this seems unlikely to change at a constant rate. The rate depends on many things but in particular on the market's valuation of existing cars in relation to new cars and upon the pattern of valuations attached to all vintages. Since most new car buyers already own a car (some 91 per cent in the UK in 1970) factors such as credit availability can affect timings of purchases and, hence, the rate of depreciation. With the growth of company car ownership in recent years, changes in the tax system also seem relevant. Thus, given these 'shocks' to the system, it seems very unrealistic to assume stability in the depreciation rate.

A recent approach to the new car market which attempts to avoid the inherent problems of the stock adjustment models, and which emphasises the role of the replacement market, is that developed by


Armstrong and Odling-Smee (39) and applied to the UK car market.

Normal replacement demand is treated as a function of past purchases of new cars and the level of exogenous socio-economic influences, but abnormal replacement is seen to depend upon changes in the levels of the socio-economic variables. (The latter representing attempts by people to adjust their ownership pattern, which has become sub-optimal, to the new situation.) Net investment depends upon both the level of, and changes in, the exogenous variables. Thus we have

\[ Q_t = \sum w_v Q_{t-v} + n(Z_t) + a(Z_t - Z_{t-1}) \]  

Eq. 3.30

where the \( w \)'s are weights attached to purchases in previous time periods and \( n \) and \( a \) are, respectively, functions indicating normal and abnormal replacement demand.

In addition to developments of the basic stock adjustment principle, a number of other approaches to modelling new car demand exist. Smith (40) for example, in his thorough study of the American car market, emphasised that the model form which would prove most effective depended crucially on the time scale of forecast required, with the unaugmented use of econometric models of the type just discussed being of value only in the medium and long term. Other authors have sought to develop even these models from a point of view different from the normal stock adjustment approach. Cramer and van der Vlis (41) developed a model of the Dutch car market in


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which the existing stock of cars is confronted with four separate demand functions. Together, the system determines the levels of both new car sales and secondhand prices as endogenous variables. The demand functions are based on log-normal Engel curves for 'first' and 'second' cars, both further subdivided as 'all cars' and 'new cars', which shift under the influence of trend variables (including a generation effect due to greater familiarity with cars among the young), the running costs of old and new cars, and the substitution induced by the ratio of new to used car prices.

To the transport planner the underlying philosophy of the stock adjustment approach raises a number of doubts as to its usefulness at anything but the most aggregate level. The model implicitly assumes a representative consumer with deterministic behaviour with a demand function assuming in its strictest sense a consumer selecting amongst continuous levels of quantity of homogeneous goods. This framework is not suited to goods such as cars which involve discrete purchase decisions and are not homogeneous. The approach also implicitly assumes a perfect car market, with a discounted annual depreciation user cost as the appropriate measure of price - such perfection does not exist. The implication of the assumed scrappage mechanism is that vehicle owners are achieving an optimum utility from the flow of services they are getting from their car; this is a strong assumption.
3.5 Econometric Models: Applied Work in the United Kingdom

In the U.K. work similar to that of Chow (42) was done by the National Institute of Economic and Social Research (43). Although their predictions (in 1961) proved to be relatively accurate, the 1967 article showed that this was due to chance since errors in estimating the explanatory variables were cancelling out errors that would have been made in the predictions if the actual values of the explanatory variables had been known. Later, more sophisticated, work by Armstrong (44) yielded predictions which also appear to be subject to massive errors although it must be admitted that the whole economic situation was by then very confused. Such studies will be of use to the government and others who wish to predict the effect of changing a particular variable, such as hire purchase restrictions. The principle aim of these models is to estimate the demand for new cars, rather than the stock of cars.

3.5-1 The Category Analysis Approach

A more promising line of approach for the urban planner is the category analysis technique. This was initially used by Wootton and Pick (45) in a study of trip generation. This technique involves the construction of a multi-dimensional matrix with each dimension

43. See Dicks-Mireaux, op. cit., and the revisions in O'Herlihy, op. cit.
44. Armstrong, op. cit.
representing an independent variable whose values are grouped into a number of discrete classes (categories). For example, if the independent variable is income the classes might be £0-£999, £1000-£1999, etc. They need not be of equal width, nor need they be numerical, e.g. the variable population density may be defined with classes 'rural', 'suburban', 'urban', etc. These classes are then used to cross-classify households and the average car ownership level for households exhibiting a particular set of characteristics is noted. This value is assigned to the 'category cell', and forecasting is then simply a matter of estimating the future number of households which are going to fall in each category cell.

The Greater London Council (GLC)\(^{46}\) category analysis model is probably the best known application of this technique to car ownership forecasting. It used three variables: income, residential density, and employed residents per household to make predictions for 1981 and 1991. It modified the procedure by introducing a saturation level of car ownership as a constraint, and by replacing income by a new variable, car-purchasing income. We shall look at these two modifications in turn.

Firstly, the saturation level. Since Tanner's 0.45 is a national average it would be too low to use as a 'ceiling'. Instead the GLC model initially calculates the probable number of driving licence holders in the forecast year by assuming that 95% of men and

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80% of women will be able to drive. This gives a saturation level in terms of the number of qualified drivers of 0.60 after allowing for the two ends of the age spectrum. If it is assumed that every qualified driver will sooner or later buy a car then 0.60 will also be the saturation level for cars per head. Adjustments to allow for an increasing proportion of children and elderly people in the population reduce this level to 0.55. Purchases of two cars by an individual are ignored. To further allow for the increased impact of congestion and limited parking facilities an upper limit of 1.6 cars per household is imposed.

Although the effect of these arbitrarily chosen numbers on predictions is arguably not very great, particularly for the earlier of the two prediction dates (1981) considered by the GLC, it should be noted that the practice runs counter to the methods of economic analysis. We would want to know why it is thought that this upper limit of 1.6 cars per households (aggregated over some area, naturally) should be thought to hold for 1981 and for 1991. Similarly, why should only 80% of women be thought capable of driving, compared to 95% of men? Finally, why should all those capable of doing so be assumed to become qualified drivers and buy their one car each?

The second modification, again following the Wootton and Pick paper, was to replace straightforward income extrapolations by a new variable 'car-purchasing income'. This only affects the income projections used in the forecasting and consists of adding the percentage fall in car prices to the normal forecast of income growth. For example, the top income groups were assumed by Mogridge and
Eldridge in their GLC work to buy new cars. The price of new cars in real terms (i.e. deflated by the retail price index) was falling by 1.3% p.a. Incomes generally were growing at 2.3% p.a. Hence 'car-purchasing income' is calculated as rising at a rate of 3.6% p.a. (47)

Again, this procedure appears to be rather arbitrary and short on economic justification. (48) The problem is to decide how much weight to attach to each of the two effects. Bates (49) using time series data, argued that income should be weighted approximately three times as much as car prices. However, this gives an inadequate explanation of the rate of car ownership increase between 1959 and 1966, and so Mogridge's one-to-one weight was used when predicting car ownership rates in 1970 from 1966 data. (50) However, car prices had actually increased over the period by approximately the same rate as money incomes. Returning to his previous weightings, Bates still found that he was excessively underestimating the growth rate of car ownership:

"Most studies which use the category analysis method are forced to increase the income growth rate by some arbitrary amount, which is called an allowance for the car price effect and is typically of the order of 2.5% p.a. But ..., in the short term at any rate, this assumption about the effect of car prices is not justified."

47. Lower income groups, buying secondhand cars which were falling in price more quickly, therefore had a higher rate of growth of car-purchasing income.


3.5-2 The Quasi-Logistic Approach

Trying to explain the continued flow of under estimations, Bates applied a 'quasi-logistic curve' to information obtained from the 1965 National Travel Survey, postulating a suitable relationship to be of the form:

\[ \log \left( \frac{P_o}{1-P_o} \right) = a + b \log Y \quad \text{Eq. 3.31} \]

where \( Y \) is income at current prices, and \( P_o \) is the probability of a household not owning a car. Rearranging 3.31 gives

\[ P_o = e^{ab} (1-P_o) \quad \text{Eq. 3.32} \]

and if we let the constant \( e^a = c \) we have

\[ P_o = cy^b (1-P_o) \quad \text{Eq. 3.33} \]

whence

\[ P_o = \frac{cy^b}{1+cy} \quad \text{Eq. 3.34} \]

Equations 3.33 and 3.34 can be compared with the equivalent equations for the ordinary logistic form:

\[ P_o = ce^{bY} (1-P_o) \quad \text{Eq. 3.35} \]

\[ P_o = \frac{ce^{bY}}{1+ce^{bY}} \quad \text{Eq. 3.36} \]

Although the two forms look similar they differ in an important respect. The first differential of the logistic curve can be expressed as a second order function of only one of the variables (in our case \( P_o \)), whereas for the quasi-logistic curve the differential is also a function of the second variable (in our case \( Y \)).
We can see this by first differentiating the logistic curve 3.35

\[ \frac{dP}{dY} = bce^{\gamma} \left(\frac{1-P}{1-P_o}\right) - c\gamma b \frac{dP}{dY} \]

\[ \therefore \quad \frac{dP}{dY} = bP_o \left(\frac{P_o}{1-P_o}\right) \quad \text{using 3.35} \]

\[ \therefore \quad \frac{dP}{dY} = bP_o \left(1-P_o\right) \quad \text{Eq. 3.37} \]

Similarly for the quasi-logistic curve we differentiate 3.33

\[ \frac{dP}{dY} = bce^{\gamma} (1-P) - \gamma b \frac{dP}{dY} \]

\[ \therefore \quad \frac{dP}{dY} = bP_o \left(\frac{P_o}{1-P_o}\right) \quad \text{using 3.33} \]

\[ \therefore \quad \frac{dP}{dY} = \frac{bP_o(1-P_o)}{Y} \quad \text{Eq. 3.38} \]

Bates estimates equation 3.31 from zonally aggregated cross-section data for households. It is the zonal aggregation which distinguishes this approach from the disaggregate methods considered in 3.5-3.

This procedure is known as logit analysis and a textbook description of it is given by Theil,\(^{(51)}\) who says:

"Regarding the estimation of the parameters of [3.31], consider first the case in which the sample consists of \(n_1\) families with income \(x_1\), \(n_2\) families with income \(x_2\), and so on. For each of these groups, one can then replace the probability in the left-hand side of the

\[ 51. \text{H. Theil, Principles of Econometrics (North Holland), 1971, p.632.} \]
equation by the observed relative frequency of car purchase and estimate \( a \) and \( b \) by the weighted least square method.

... When the incomes of the families are different, one may group the observations in income brackets and neglect the income differences within groups when these are not too large."

Results from some models using quasi-logistic analysis are presented in Table 3.3. Since \( b \) is (normally) negative, it is easier to interpret the results if we rearrange 3.34 as follows:

\[
P_o = \frac{c}{Y^{-b} + c}
\]

Eq.3.39

We can now see that as income approaches zero, \( Y^{-b} \) will approach unity. As income rises, \( Y^{-b} \) increases and therefore \( P_o \) falls. This is represented diagrammatically in Figure 3.7.

![Figure 3.7](image.png)

Interpretation of the coefficients of equation 3.31 is complicated by interdependencies. It is clear that the negative value of \( b \) represents the negative income elasticity of the odds in favour of
For compactness we denote \( \log \left( \frac{P}{1-P} \right) \) by \( \text{LO} \); log household income by \( \text{LY} \), log population/residential density by \( \text{LD} \), log of persons per household by \( \text{LH} \), log of bus and rail transport variables by \( \text{LB} \) and \( \text{LR} \) respectively, and log of socio-economic group variables by \( \text{LC} \). \( t \) statistics are given in brackets, where available.

**BRISBOURNE** 1965 National Transport Survey

\[
\text{LO} = 0.097 - 2.384 \text{LY} + 0.307 \text{LD}
\]

\[ (37.14) \quad (12.31) \quad R^2 = 0.97 \]

**BATES** Family Expt. Surveys and National Transport Surveys

**F.E.S.** 1964 \( \text{LO} = 9.146 - 2.716 \text{LY} \)

\[ R^2 = 0.93 \]

1965 \( \text{LO} = 7.023 - 2.098 \text{LY} \)

\[ R^2 = 0.96 \]

1966 \( \text{LO} = 6.774 - 2.030 \text{LY} \)

\[ R^2 = 0.99 \]

1967 \( \text{LO} = 7.752 - 2.268 \text{LY} \)

\[ R^2 = 0.93 \]

1968 \( \text{LO} = 6.142 - 1.821 \text{LY} \)

\[ R^2 = 0.93 \]

1969 \( \text{LO} = 5.814 - 1.780 \text{LY} \)

\[ R^2 = 0.93 \]

**N.T.S.** 1965 \( \text{LO} = 6.906 - 2.159 \text{LY} \)

\[ R^2 = 0.99 \]

1966 \( \text{LO} = 6.882 - 2.193 \text{LY} \)

\[ R^2 = 0.98 \]

**FAIRHURST** London Transportation Study 1962

\[
\text{LO} = 10.5 - 2.2 \text{LY} - 3.0 \text{LH}
\]

\[ (17.4) \quad (12.8) \quad R^2 = 0.72 \]

\[
\text{LO} = 5.02 - 1.58 \text{LY} - 0.705 \text{LH} + 0.227 \text{LB} + 0.125 \text{LR}
\]

\[ (11.69) \quad (1.9) \quad (4.13) \quad (3.42) \quad R^2 = 0.80 \]

\[
\text{LO} = 1.32 - 1.2 \text{LY} + 0.59 \text{LD}
\]

\[ (8.48) \quad (15.68) \quad R^2 = 0.78 \]

\[
\text{LO} = 3.3 - 1.3 \text{LY} - 0.358 \text{LH} + 0.159 \text{LB} + 0.087 \text{LR} + 0.22 \text{LR}
\]

\[ (8.05) \quad (0.92) \quad (2.62) \quad (2.24) \quad (2.25) \quad R^2 = 0.81 \]

**BUTTON** (unpublished 1972) West Riding Local Authorities 1967

\[
\text{LO} = -2.284 + 0.478 \text{LC} - 0.0965 \text{LD}
\]

\[ R^2 = 0.91 \]

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**Table 3.3**

Results from Some Models Using Quasi-Logistic Analysis \((52)\)

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there not being a car purchased, which is a sensible result. The ratio $\left( -\frac{a}{b} \right)$ is the logarithm of that income at which the household is as likely or not to own a car (the equal probability income). This may be seen by putting $P_o = \frac{1}{4}$ in equation 3.31. By varying $a$ and $b$ it is possible to examine the effect of holding $\left( -\frac{a}{b} \right)$ constant. Empirical evidence produced by Bates tends to support the hypothesis of constancy of this ratio over time, with the value of $b$ gradually falling in absolute value. Graphically this will move us (over time) in Figure 3.7 from the original curve (0) to the intermediate curve (1). Here the spread of car ownership is less unequal. Households with income less than the equi-probability level have become more likely to own a car, and vice versa. A possible reason for this would be if the price of older cars were to fall relative to newer ones.

Further, if $a$ is held constant, then the empirical evidence supports an upward movement of $b$ with the result that there is a dropping of the $P_o$ curve over its extra length. This movement may be due to either a general shift of the price level in the car market vis-à-vis other markets or to changes in consumer tastes (which introduces the ideas of consumer acceptance, etc.). The combination of these two effects working together on the overall value of $b$ is uncertain unless we accept Bates' proposition that $a$ is likely to fall through time. If this is true then we may expect the 'final' curve to take the form shown in Figure 3.7 as curve 2.

The advantage of this approach over others is that it separates two distinct effects. It distinguishes, and isolates, the effects of the car market as a whole vis-à-vis all other forms of expenditure.
and at the same time recognises and incorporates the influences of the price/age structure inside the car market. In subsequent work, the model is extended to cover an additional variable - residential density - and developed to explain the activities of single and multiple car households. It is found that the best explanation of ownership rates for single ($P_1$) and multiple ($P_2$) car owning households is obtained from:

$$\frac{P_2}{P_1} = a_1 e^{-b_1 Y D c_1} \quad \text{Eq. 3.40}$$

$$P_0 + P_1 + P_2 = 1 \quad \text{Eq. 3.41}$$

where $D$ is the number of persons per acre (resident).

The introduction of the residential density variable now calls for some comment. As we noted in the previous section, residential density is used as a proxy for a number of other factors - factors such as public transport availability, congestion levels, parking restraints, etc. We have noted above that the density level may have some effect on national saturation levels but this does not automatically mean that it is an appropriate variable to incorporate into an econometric model of car ownership in a discrete area. As an explanatory variable it is imprecise and its influences multifarious. In addition, residential density is closely correlated with income, and, to a lesser extent, household structure and such relationships may lead to problems when allocating households to the various categories.

It may be useful to replace residential density with a variable more directly related to the influences that the planner is seeking to include in his model. Some form of accessibility index may fulfil this role. In its simplest form accessibility is seen as an indicator of 'ease of access' as can be found in Savigear's 'naive' index developed for Oxford. The shortcomings of such a limited approach (the need for a full origin-destination matrix on the practical side and the neglect of the relative attractiveness of alternative destinations on the theoretical) have led to the use of indices measuring the quality of public transport in the zone (see also Chapter 6).

The Quarmby/Bates model has been extended to incorporate a crude accessibility index by Fairhurst. Using data collected as part of the London Transportation Study aggregated to the level of the traffic district to minimise the within zone variance, Fairhurst tested a model of the form:

\[
\log\left(\frac{P_0}{1-P_0}\right) = c + b \log Y + d \log H + f \log (B+1) + g \log (R+1)
\]

Eq. 3.42

where \( P_0 \) is as before,

\( Y \) is household income,

\( H \) is persons per household,

\( B \) is a bus public transport index,

and \( R \) is a rail public transport index.


55. Fairhurst, op. cit.
The public transport accessibility indices in this case were extremely naive taking the form:

\[ \frac{E}{\sum_{i} \frac{N_{ij}}{A_j}} \]

Eq. 3.43

where \( A_j \) refers to the acreage of district \( j \) and \( N_{ij} \) to the mid-day frequency of public transport service \( i \) in zone \( j \). Essentially this is an "ease of access" variable, but its exclusive concentration on public transport ignores the effects of vehicular congestion on car ownership, and its dependence on mid-day services neglects important peak-flow considerations. This latter point is important to the extent to which cars are bought primarily as a means of travelling to work. Some of Fairhurst's results are included in Table 3.3.

D.J. Parish\(^{(56)}\) criticises the Bates type model because of its treatment of saturation levels of car ownership. He says that if incomes rose sufficiently there would come a point where the model would predict that every household would own two or more cars. Not being able to make the required adjustments necessary to introduce saturation levels, Parish goes on to estimate quasi-logistic models using a measure of permanent income instead of the normal income variable. He proxies permanent income by household expenditure, and where these data are not available uses a gamma distribution technique with 'borrowed' parameters. The results are not comparable with those in Table 3.3.

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3.5-3 The Regional Highway Traffic Model Approach

The work of the car ownership group of the Regional Highway Traffic Model Project (RHTM) found favour with the Leitch Committee and forms one basis for the latest official government car ownership projections. Their approach follows that adopted in several local level transportation studies in the United States by using a 'micro' method, relating car ownership to a set of 'causal' variables. It differs from the quasi-logistic approach in that there is no attempt at spatial aggregation. Briefly, a log-logistic curve is fitted to the proportion of households with one or more cars, \( P(1+) \), and a simple logistic curve is fitted to the proportion of car owning households who own two or more cars, \( P(2+/1+) \). At the national level the only independent variable is an income variable.

Initially the equations were fitted to Family Expenditure Survey (FES) data for a given year, say \( t \), giving

\[
P_t(1+) = \frac{S(1+)}{1 + e^{-a_1(t)Y_t - b_1(t)}} \quad \text{Eq. 3.44}
\]

\[
P_t(2+/1+) = \frac{S(2+/1+)}{1 + e^{-a_2(b) - b_2(t)Y_t}} \quad \text{Eq. 3.45}
\]

where \( Y_t \) is gross household income

- \( S(1+) \) is the saturation level of \( P(1+) \)
- \( S(2+/1+) \) is the saturation level of \( P(2+/1+) \)

57. This subsection draws upon material contained in Button, Fowkes and Pearman (1981), op. cit.


and the $a_1(t)$, $a_2(t)$, $b_1(t)$, $b_2(t)$ are estimated coefficients for the equations with data for year $t$.

At first the $S(1+)$ and $S(2+/1+)$ were assumed fixed and just the $a$ and $b$ parameters were estimated. For the years 1969-75 statistical tests showed the parameter vectors $(a, b)$ to be significantly different over time for each equation. However, taking the parameters individually the $b_1(t)$'s in 3.44 and the $a_2(t)$'s in 3.45 were found not to be significantly different over time. The next step was to deflate the income variable by a car price index, $P_t^c$, after which the $a_1(t)$'s and the $b_2(t)$'s were also found to be non-significantly time variant. This gives an equation which is stable over time.

For this 'time-stable' model, $S(1+)$ and $S(2+/1+)$ were estimated to be 0.948 and 0.563 respectively, but these values were replaced by 'rounded' values not statistically different, giving the final form:

\[
P_t^{(1+)} = \frac{S(1+)}{1 + e^{-a_1 Y_t - b_1}} \quad \text{Eq. 3.46}
\]
\[
P_t^{(2+/1+)} = \frac{S(2+/1+)}{1 + e^{-a_2 - b_2 (Y_t/P_t^c)}} \quad \text{Eq. 3.47}
\]

where $\frac{Y_t}{P_t^c}$ is mean household gross income, in money terms (£pw FES) deflated by an index of car prices, and is referred to as 'Car Purchasing Income'.

and the estimates of the parameters are

\[
\begin{align*}
    a_1 &= -7.757, \quad b_1 = 2.260, \quad S(1+) = 0.95 \\
    a_2 &= -3.764, \quad b_2 = 0.4492, \quad S(2+/1+) = 0.60
\end{align*}
\]
For 3.47 the calibration used the year 1969 - 75, while for 3.46 the years 1965 and 1966 were used in addition. Figure 3.8 shows implied future levels of car ownership using various assumptions about car purchasing income. The future values are based on the assumption that income distributions will follow approximately a gamma distribution, i.e.

\[ p(X) = \left( \frac{\alpha}{\Gamma(n+1)} \right)^{-\alpha} X^{n-1} \]

\[ \text{Eq. 3.48} \]

with \( n \) taken to be constant over time (taken to be 1.58). This parameter controls the 'shape' of the distribution and, so, once the mean is known, the whole distribution is specified. By making varying assumptions about the future growth of mean incomes, the future numbers of households owning 0, 1 and 2+ cars can be obtained.

Census evidence gives the conversion to cars per head as

\[ C_p = P(1) + 2.169 P(2+) \]

\[ \text{Eq. 3.49} \]

To estimate cars per household, \( C_h \), the following forecasts of household size are employed:

- 1980 - 2.65 persons per household
- 1985 - 2.58 persons per household
- 1990 - 2.53 persons per household

with no further changes currently assumed.
Figure 3.8
Car ownership growth assuming different levels of increase in car purchasing income

The RHTM method raises a number of issues:—

(i) The functional forms of equations 3.46 and 3.47 have relatively little theoretical or empirical underpinning. The log-logistic form 3.46 has been employed quite frequently, but even here there is little evidence that it is significantly superior to the simple logistic. The simple logistic has to account for the sum of all the sigmoid distributions after that for $P(1^+)$. Furthermore, in the longer term, as the number of households owning more than two cars ceases to be insignificant, it is desirable to predict not just $P(2+/1^+)$ but also the average number of cars these households have. This cannot be assumed to remain close to 2.169, as is implied if equation 3.49 were
to be used for long term forecasting.

(ii) A problem of all 'causal' models which are required to provide forecasts is the necessity of forecasting the growth curves of the explanatory variables 'causing' the change in the modelled variable. This is straightforward when the explanatory variables are following a clearer growth path than the modelled variable, but this is not the case here. Rather, we might envisage car ownership as growing more 'steadily' than its 'causes'. In other words, if some part of car ownership growth could be apportioned to the passage of time, rather than to long term trends in GDP, household size, population density levels, public transport provision, etc., then the predictions obtained should be less susceptible to errors in the predictions of these 'causes'.

(iii) The explanatory variables may have interactive effects. Richer households tend to have more members, to live in less densely populated areas with lower public transport accessibility, etc. The RHTM work found, after allowing for income variation, that household size was unrelated to P(1+) or P(2+/1+). Bigger households tended to have more cars, but this could be explained by their higher incomes, rather than by their size, per se, i.e. the tendency was induced by an income effect. Fowkes, Pearman and Button,\(^{60}\) however, found that the number of household residents and household income had complicated interactive effects when related to household car owner-

ship. For richer households, increasing household size reduced car ownership, while for poorer households, the reverse was true. This was particularly the case when the indicator of household size was the number of employed residents, Z, suggesting that, for low household incomes, even the increased level of car ownership is still so low that it is in some sense a 'necessity' as E increases, whereas at high household incomes, increasing E implies lower income per head and a reduction in the amount of income available for 'luxuries' such as increased car ownership beyond the high level typical of these income groups. If we predict the income distribution to rise over time, all income groups will come to regard additional car ownership as a luxury and previously calibrated 'aggregate' equations 3.46 will become obsolete.

When justifying a saturation level for P(1+) which is less than one, Bates, Gunn and Roberts (61) argue that "The FES data ... shows that the highest observed value for P(1+) in any of the reported income groups was 0.951". However, in addition, households in such groups are likely to have other attributes which would induce them to own more cars than dictated by their income alone. Hence there is likely to be a missing variable problem, or one of multicollinearity. This is not likely to be too serious a problem if the collinear or omitted variables maintain a fixed relationship with income over time. However, in the car ownership case, these variables are likely to include locational ones. As the population becomes richer, it seems unlikely that it will be possible for everybody to locate in low density suburbs so, in fact, the relationship between income and density is likely to change.

If this kind of possibility is not recognised and modelled appropriately, then there is a danger that incorrect estimates of elasticities and saturation levels will be obtained. For example, in Figure 3.9, income and density are highly correlated in a situation where two separate curves should be fitted for households living in areas of different population density, then mistakenly fitting a single curve through the observed points will lead to an over-estimation of the income elasticity and saturation level. This is because the inverse relationship between income and density causes the observed points to trace out a steeper curve than the 'true' curves and reach saturation at or about the saturation level of the upper curve rather than at a weighted average of the saturation levels of the two 'true' curves.

For these reasons it seems more appropriate that separate equations should be fitted to different household types. Work of this kind has shown\(^{(62)}\) that the income elasticity of car ownership is lower for larger households than for smaller ones, although the fitted curve starts off higher.

![Diagram showing the omitted variable problem](image)

**Figure 3.9**

The omitted variable problem

(iv) The nature of the proper income variable is still not adequately understood. The RHTM team undertook thorough statistical testing before deciding to use the 'Car Purchasing Income' measure previously championed by Mogridge. Here money incomes are deflated not by the retail price index (which would give real incomes) but by an index of car prices. The implicit assumption when using this measure is that households regard a proportion of their income as being available for car purchase/ownership and subject to negligible cross elasticities with respect to other uses. Hence a 1% increase in money income would increase the number of cars which would be purchased/owned by 1% if car prices remained constant. If car prices fell by 1% but money income remained constant, the result would be the same.

Bates had previously criticised such adjustments to income on the grounds that they were just a device to avoid the underestimations of the growth of car ownership which had occurred previously when cross-sectional income elasticities had been used for forecasting. The question is essentially an empirical one, but the particular years chosen for the RHTM analysis, 1969-1975, with the 'odd' years 1965 and 1966 added on, were probably more than usually favourable to the car purchasing income hypothesis.

3.5-4 'Hybrid' Extrapolative/Economic Models of Car Ownership

Hybrid car ownership models essentially attempt to capture the

63. Mogridge and Eldridge, op. cit.
64. Bates (1971), op. cit.
65. This section draws heavily on Button, Pearman and Fowkes, op. cit., pp.20-26.
theoretical advantages and policy sensitivity generally associated with economic approaches to demand analysis with the simplicity and ease of application normally reserved for the extrapolative approach. Here, we focus our attention specifically on more recent work at the Transport and Road Research Laboratory which has attempted to construct such hybrid models of the national car market. We have already briefly encountered some of this work (i.e. equation 3.11) but here it is appraised more fully and the more recent developments assessed.

The TRRL forecasts prepared in 1974(66) attempted to meet complaints that (a) the extrapolative framework led to self-fulfilling prophecies since they were used to support road building which in turn encouraged more traffic and thus validated the forecasts,(67) (b) the models used were insensitive to changing socio-economic conditions, especially the rising costs of motoring and (c) were producing poor predictions of car ownership (see Table 3.3) - it should be noted that these complaints lacked an internal consistency! The model used (and here presented in its simplest form) was:

\[
C_t = \frac{S}{1 + bY^a - fs - gs - aSt} \quad \text{Eq. 3.50}
\]


67. This point was strongly put by M. Senior (Driving into the future, Ecologist, Vol.5, 1975, pp.341-3) when he said, "the forecasts are true only if the road building programme continues. The road building programme will continue only if the forecasts are true. If one is assumed then the other follows. If either is denied then both collapse". A similar point is made in J. Gershuny:-- Transport forecasting: fixing the future, Policy and Politics, Vol.6, 1978, pp.373-402.
<table>
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<th>Year of publication</th>
<th>Base year for calculation</th>
<th>Cars per person</th>
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<td>1.84</td>
</tr>
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<td>1974</td>
<td>1972</td>
<td>0.23</td>
<td>0.26</td>
<td>(Actual = 0.25)</td>
</tr>
</tbody>
</table>

Table 3.3
Comparison of National Car Ownership Projections Using TRRL Extrapolative Technique with the Actual Figure for 1975

Here \( Y \) is per capita income measured as GDP, in real terms, divided by population.

\( PM \) is a measure of real motoring costs in terms of the consumer's expenditure deflator for the purchase and running of motor vehicles divided by the deflator for all goods and services.

Such a model permits the rate of approach to saturation to be influenced by income and motoring costs, but not the ultimate saturation level itself. Clearly this revised model incorporates additional parameters to be estimated, with \( f \) and \( g \) being determined exogenously and then fed into the equation. This is possible as a result of the following differentiation and manipulation of equation 3.50:

141.
Let $K = bY - f_{PM} - gS - aSt$

\[
\frac{dK}{dt} = K(-aS - bY \frac{dY}{dt} + gS \frac{dPM}{dt}) = KR S
\]

where $R = a + f \frac{dY}{dt} + g \frac{dPM}{dt}$

From 3.50

\[
C_t = \frac{S}{1 + K}
\]

\[
\frac{dC_t}{dt} = -\frac{dK}{dt}S / (1 + K)^2 = \frac{S^2 R (S/C - 1)}{S^2 C}
\]

\[
G_t = \frac{1}{C_t} \frac{dC_t}{dt} = R (S - C_t)
\]

\[
= (S - C_t) (a + f \frac{dY}{Y dt} + g \frac{dPM}{PM dt}) \quad \text{Eq. 3.51}
\]

Since $G_t$ is the rate of growth of $C_t$, and $\frac{f \cdot dY}{Y \cdot dt}$ is the rate of growth of $Y$, it follows that $f (S - C_t)$ must be the income elasticity of demand for car ownership and $g (S - C_t)$ the cost of motoring elasticity of demand. Consequently, if the elasticities are 'known', then $f$ and $g$ can be estimated for a given $S$ for any level of per capita car ownership. The parameter $a$ reflects the influences of all factors other than income and motoring costs on car ownership. The elasticities used in the TRRL work were hybrids of long-term parameters (taken from cross-section studies across households within the UK) and short-term parameters (based upon British time series data). While the cost elasticity was based upon a crude averaging of the long and short-run parameters, with supplementary sensitivity analysis the income elasticity was closer to the long-run estimate again with supplementary sensitivity analysis being applied.
Calibration of the revised logistic model can be performed non-linearly directly on equation 3.50. Otherwise, it is necessary once again to estimate $S$ first, as well as $f$ and $g$. Then, by transforming equation 3.50 to

$$\log_e \left( \frac{C_e}{S - C_t} \right) - f_s \log_e Y - g S \log_e PM = a S + \log_e b$$

Eq. 3.52

$a$ and $b$ may be found by using a time series regression of the left-hand side of the equation against $t$.

The external estimation of $g$ and $f$, in addition to $S$, obviously poses problems:

(i) The model assumes that it is current income and motoring costs which influence ownership, whereas intuitively some form of lagged response would seem more reasonable. In addition, there may be a ratchet effect such that, although increased incomes and reduced motoring costs may increase car ownership, this higher level of ownership may not be given up if incomes and motoring costs were to return to their initial levels.

In an attempt to circumvent this problem, Tanner\(^{(68)}\) has incorporated a short-term lagged income effect to supplement the income and motoring cost variables (the actual model specification being of the power-growth form discussed below rather than the logistic specification but this does not weaken his argument). The results, however, when applied to car ownership forecasts for the target year 1995 suggest


143.
that the hybrid model is not particularly sensitive to such a modification.

(ii) Knowledge about income elasticities and, more especially, motoring cost elasticities is poor, and yet the higher these elasticities the more weight that is attached to income and motoring costs in the overall model. Using central estimates of income and motoring cost elasticities, Tanner's actual estimate of the impact of the different variables for the period 1952 to 1972 suggested that increasing income accounted for 45 per cent of the rise in car ownership, decreasing costs of motoring for 15 per cent, and other factors, as reflected in the 'catch all' variable t, for 40 per cent. However, as Bates (69) has shown, different assumptions lead to markedly different attributions, with major consequences for ownership forecasts as a result of the varying importance attached to economic factors.

(iii) There is the problem of defining the appropriate form of the variables. Tanner relied in this model upon a standard economic definition of income and compiled an index of motoring costs but these may not be the appropriate definitions for forecasting in this context. For example, other studies have suggested that 'disposable income', 'permanent income', 'car-purchasing income' or 'threshold income' may be more appropriate measures of income as it

actually influences car ownership. (70)

(iv) There is the very difficult task of predicting the future levels of per capita income and motoring costs. This posed particular problems in the early 1970s when (a) the previously assumed trend increase in real incomes (by about 2 per cent per annum) ceased, and (b) the cost of motoring, mainly due to fuel price rises, was subjected to a substantial extra-marginal increase. Whereas it may have been possible to make reasonable predictions of income and motoring costs a decade earlier, the actual period when it was felt helpful to incorporate their influence on car ownership proved to be one of great uncertainty about their future trends. Some allowance for this problem was made by offering a sensitivity analysis which to some extent indicated the impact on predicted car ownership levels of adopting differing assumptions (in effect high and low values of variables) regarding future income and motoring cost trends.

Despite these modifications it soon became clear that the revised TRRL approach was still tending to over-predict car ownership levels. In the mid-1970s this became a particularly contentious point at local public enquiries into trunk road investment plans. In March 1975 it had been announced that "the Government agrees that the need for any road scheme may appropriately be challenged at a

public enquiry, provided that matters of policy are not called into question". (71) A letter from the Council on Tribunals in August of the same year clarified this with respect to car ownership forecasts: "It appears that the DoE memorandum H3/75 (National Traffic Forecasts) is one of a series of technical memoranda which lay down design standards and assumptions to be used by the Department in drawing up road proposals. The department regards these as matters of policy" (writer's italics). Inspectors at public enquiries were duly told not to permit questioning of any traffic forecasts. The sanctity thus given to the forecasts by government, it should be pointed out, is in marked contrast to the attitude of the TRRL. Tanner and his colleagues have always been acutely aware of the problems involved in developing reliable projections of car ownership. Public pressure, however, built up and this, combined with attacks on both the quality of forecasts and the underlying rationale of the logistic curve fitting procedure, encouraged further revisions to take place.

The symmetric nature of the logistic function, in particular, was generally felt to be inappropriate. As the Leitch Committee said: (72) "there is nothing uniquely right about the S-shaped curve that determines the level of car ownership in future years". Having found the logistic curve not fitting the data, passing through the chosen saturation level, nor providing adequate predictions all at the same time, Tanner (73) added a parameter to form a power growth

73. Tanner (1977), op. cit.
function. This curve is similar to the Gompertz in that, compared with the logistic, the rate of growth slows more quickly over time, giving a slower approach to saturation. This gives a non-symmetric curve from which reasonable short-run predictions have been obtained while retaining a belief in high saturation levels in the distant future. (74)

The basic formula of the power growth function employed is:

\[ C_t = \frac{S}{1 + (b + at + f \log Y + g \log PM)^n} \]  
\[ \text{Eq. 3.53} \]

The additional parameter \( n \) reflects the degree of asymmetry; the higher the value of \( n \) the more symmetric is the curve, with the logistic being approached as \( n \) tends to infinity. The values of \( S \), \( g \) and \( f \) are again determined externally, although the values used in the 1977 forecasts were somewhat different from those of earlier work. (75) The parameters \( a \) and \( n \) are found using:

\[ C_t = \frac{n \left( S - C_t \right) \left( S - C_t \right)^{1/n} + 1/n}{S \cdot C_t^{1/n}} \left( a + \frac{g dY}{Y dt} + \frac{f}{PM} \frac{dPM}{dt} \right) \]  
\[ \text{Eq. 3.54} \]

The estimates were obtained by minimising the sum of the squares of the differences between the two sides of equation 3.54 using actual time-series values of \( Y \), \( PM \) and \( C_t \) for Great Britain.


75. See Appendix 3 for an assessment of this approach and the quality of its fit to past events.
The final parameter $b$ was found, as before, to constrain the predicted car ownership in the base year to the actual level. The forecasts obtained from the models, using high and low predictions of $Y$ and PM are shown in Figure 3.10. They are clearly lower than those produced using the logistic curve, but their accuracy cannot yet be properly assessed due to the short time lapse and difficulties with post-1974 data following computerisation of licence records.
3.6 Some Comments on Recent Official National Forecasts

The chapter has been devoted to a detailed appraisal of the alternative approaches which may be employed in car ownership forecasting, paying particular attention to those which have been used to produce national forecasts. (In Chapter 7 the respective merits of the alternatives are subjected to further consideration although there it is the practical usefulness of different modelling frameworks which is looked at.) Before leaving the review of the car ownership modelling techniques a few comments need directing at the changes in forecasting which have taken place in official policy-making in recent years. Broadly, while a decade ago a single, extrapolative framework was considered adequate, now a much more flexible approach is favoured involving the use of at least two alternative methodologies.

The findings of the Advisory Committee on Trunk Road Assessment (76) that "The Department's current methods [of traffic forecasting], because they are based on extrapolatory techniques, are generally insensitive to future policy changes. It is therefore preferable to adopt a 'causal model'" put the Department of Transport in some initial difficulty. For many years it had used (many would say far too rigidly) the TRRL forecast as the single forecast of car ownership for use as inputs to policy-making, overlooking the more circumspect view of the forecasts espoused by their authors. It was now being strongly advised to adopt a forecasting model based on a markedly different philosophy and yielding quite different results. However, the new model was clearly not proven to the extent that it could

76. Department of Transport (1978), op. cit., p.133.
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76. Department of Transport (1978), op. cit., p.133.
surplant the extrapolative approach immediately. As a preliminary compromise, the Department issued in January 1978 the *Interim Memorandum on Travel Forecasts* (77) which, responding also to the Committee's criticism of its failure to reflect uncertainty about the future by publishing a range of forecasts, gave not a single forecast, but high and low forecasts up until the year 2005 (see Figure 3.11). These forecasts were obtained by using both the RHTM and TRRL approaches, and adopting common assumptions about the inputs to the models, again using ranges of values to reflect uncertainty in GDP growth, motoring cost changes, etc. The lower band on the range of forecasts was based on the curves resulting from pessimistic assumptions, and largely follows the path of the corresponding RHTM prediction. The upper band relies on the TRRL power growth curve with optimistic assumptions, which always gave significantly higher forecasts than the RHTM model with corresponding inputs. However, since there was this consistent discrepancy, the TRRL projection was reduced a little throughout, to give the upper band shown in Figure 3.11.

The Department's inevitably hasty response clearly could not hope to command long-term respect, being heavily dependent on judgement for the balance of importance which was given to the quite different forecasts emerging from the extrapolative and causal models. In addition, the period since 1975 (the last year used in calibrating the RHTM equations) proved to be one of rising real car prices and low growth in gross income, causing the model to predict a drop in car use.

Faced with this difficulty, the Department opted to retain the
Interim Memorandum compromise of using both forms of model and of producing a range of forecasts on an essentially judgemental basis. The power growth curve was retained, although with revised assumptions about income growth and changes in motoring costs. The RHTM causal model was, however, following research within the Department, more drastically amended, with the independent variables in the model becoming gross household income deflated by the RPI, and the proportion of the adult population in possession of a full driving licence. The latter is a trend variable, which has been found to
provide a better statistical result than the previously used motoring cost index. It is not suggested that it is a totally suitable proxy for what is probably the effect of changing social attitudes to the car, but no better proxy is currently known. Both models were run with common sets of optimistic and pessimistic assumptions about the future level of prices, incomes, etc. The resulting high and low forecasts from the two models were averaged to give the upper and lower bounds on the range of car ownership forecasts in the Department's National Road Traffic Forecasts. (78)

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CHAPTER 4

THE ECONOMICS OF REGIONAL VARIATIONS IN CAR OWNERSHIP

4.1 Introduction

Having spent some considerable time examining the merits of various car ownership modelling and forecasting techniques in the previous chapter we now proceed to conduct some empirical investigations of spatial variations in car ownership rates. This chapter is concerned with regional variation within Great Britain - while Chapter 5 looks at local, urban car ownership modelling. A number of alternative techniques are employed in an attempt to explain why regional car ownership levels differ.

Geographical variations in the level of United Kingdom car ownership rates have attracted considerable attention over the years. Sleeman, for example, has periodically looked at variations in Great Britain while more limited geographical studies of England and Wales and Ireland have also been undertaken. Sanghi has


produced results for the United States. Variations in vehicle ownership are seen as useful guides to the need for transport infrastructure improvements and extensions, and are also cited as illustrative of the relative prosperity of different regions of a country. Reliable forecasts of the future levels and geographical spread of car ownership, are, therefore, important components of both regional policy-making and transport planning. Most of the vehicle ownership studies are, however, now somewhat dated (Buxton and Rhys, for example, relied upon data for 1969 and 1970 while McCarthy's study stopped at 1969) especially in view of the changed economic environment of the 1970s. Here we attempt to up-date the situation by both employing slightly more sophisticated statistical techniques than some of the other studies and also by using more recent data sources. The study concentrates exclusively on the British situation and ignores Northern Ireland. Rising fuel prices, the adoption of new transport policies at the local and national level (especially following the 1968 Transport Act) and the poor (macro-economic) performance of the British economy over the past decade are all likely to have exerted influences on ownership patterns, thus many of the parameters derived by earlier workers in the field are likely to have changed significantly.

4.2 The General Situation in Great Britain

As can be seen from the index shown in Table 4.1 there has been more than a four-and-a-half-fold increase in the national level of per capita car ownership over the twenty-five years to 1978 although it is equally clear that there have been quite substantial differences
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(*Adjustments have been made to the base data for those regions whose boundaries were affected in April 1974 by the Local Government Act 1972. Additionally it should be noted that centralised licensing was adopted in 1976 replacing local authority registration. Hence the 1978 data is not strictly comparable with previous years.)

Table 4.1

The Growth of Per Capita Car Ownership in the Regions of Great Britain 1953 to 1978 (1953 = 100)

between the British regions in their growth rates. The fastest growing regions, the North West and North have, for example, enjoyed a more than 500 per cent increase in per capita ownership while the South West and East Anglia have had less than a 400 per cent rise. Much of this discrepancy is explained by the low base ownership levels in the North West and North. (43 cars and 41 cars respectively per 1,000 inhabitants in 1953 compared with the national average of 56 per 1,000 inhabitants) although Scotland, with the absolute lowest level of ownership 25 years ago, has experienced a somewhat slower growth.
Despite the more rapid growth in ownership enjoyed by regions with initially low levels, there have been very little variations in the actual ranking of regions. The only changes in rank order between 1953 and 1978 were Wales overtaking the East Midlands into fifth place in the table and the South East moving East Anglia at the top. (The Spearman's rank correlation coefficient comparing the two years is found to be 0.89.)

The more recent growth paths of regional per capita car ownership (since 1965) are seen in Figure 4.1. The consistency of ranking

![Figure 4.1](image)

*Figure 4.1*

*Growth of car ownership in the regions of Great Britain*
is once again quite apparent but, in addition, a number of other features emerge. The upward trend in ownership throughout the 1960s and 1970s quite clearly tapers off towards the end of the period in all regions and the comparison made earlier between 1953 and 1978, in fact, fails to reflect the differences in ownership which existed when ownership was at its peak in most regions (i.e. 1976). The marked absolute downturn in 1978 (there are no figures available for 1977) seen in all regions may either be attributable to statistical discrepancies or real economic forces. Changes in regional boundaries created by the 1972 Local Government Act (effective from 1974) plus the adoption of centralised registration are likely to have exerted a small effect which cannot be completely allowed for.\(^6\) Data problems are, however, unlikely to be the entire explanation of the downturn in ownership in 1978. It seems that the rising cost of motoring is likely to have begun to exert an influence on aggregate ownership levels. There were also the short term effects of the recent, generally poor, economic performance which have been reflected in a fall in real income and a depressed level of expectations about future well-being.

6. Some indication of more general difficulties in using official data on car ownership is seen in the following table based on the three main statistical sources available. The three main series are based on licence data, the Family Expenditure Survey and the General Household Survey and reveal marked differences in the levels of ownership.

<table>
<thead>
<tr>
<th>Year</th>
<th>Licences (GB)</th>
<th>FES (UK)</th>
<th>GHS (GB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1969</td>
<td>0.2089</td>
<td>0.1949</td>
<td>-</td>
</tr>
<tr>
<td>1970</td>
<td>0.2137</td>
<td>0.2013</td>
<td>-</td>
</tr>
<tr>
<td>1971</td>
<td>0.2231</td>
<td>0.2024</td>
<td>-</td>
</tr>
<tr>
<td>1972</td>
<td>0.2345</td>
<td>0.2124</td>
<td>0.2171</td>
</tr>
<tr>
<td>1973</td>
<td>0.2483</td>
<td>0.2250</td>
<td>0.2327</td>
</tr>
<tr>
<td>1974</td>
<td>0.2508</td>
<td>0.2371</td>
<td>0.2391</td>
</tr>
<tr>
<td>1975</td>
<td>0.2429</td>
<td>0.2441</td>
<td>0.2443</td>
</tr>
<tr>
<td>1976</td>
<td>0.2585</td>
<td>0.2434</td>
<td>0.2485</td>
</tr>
<tr>
<td>1977</td>
<td>-</td>
<td>0.2515</td>
<td>0.2567</td>
</tr>
</tbody>
</table>

Estimates of Trends in Cars per Person

157.
It is also noticeable from Figure 4.1 that a consistent pattern of regional ownership emerges; in effect the nation can be divided into three distinct groups of regions, the South West, South East and East Anglia having the highest propensity for ownership, the West Midlands, Wales and East Midlands form a middle grouping, while the North West, Yorkshire and Humberside, the North and Scotland fall into the lowest ownership category. This trend of lower car ownership levels as one moves further north has been observed in previous studies (i.e. by Tanner (7) using U.K. county data and by Bates, Gunn and Roberts (8) using disaggregated household data) but no really satisfactory explanation of the phenomenon exists. Tanner did in fact make some general comments about climatic variation but did not substantiate these empirically. Other tentative explanations include possible differences in the quality of public transport systems. Dummy variables have been employed in econometric models to allow for the feature and to improve the statistical quality of models but such mechanical devices cannot explain it. (9) They are also of dubious use in forecasting if the changes in the underlying causal relationship are not reflected accurately by the dummies.


There is some recent evidence\(^{(10)}\) that up to 1976 the per capita levels of car ownership at the regional level were converging towards the national average, albeit at a very slow rate. The more recent information for 1978 is that this convergence process has halted and that a degree of divergence, particularly with regard to the North and Scotland, has emerged. Clearly a one year sample cannot be conclusive on this point but the level of car ownership in the northern regions has fallen sharply compared with the national average.

New boundaries introduced in 1974 make it impossible to form long-term temporal comparisons with past car ownership patterns at the sub-regional level. Table 4.2 gives the breakdown of ownership by county according to region. It is apparent that the dispersion of ownership within a region tends to be relatively small with the exceptions of Scotland and Wales which are far more heterogeneous in economic and geographical composition than the other regions. Generally, however, if a region has a high per capita level of ownership then the counties within it exhibit a similar characteristic and vice-versa.

Further, if we sub-divide the counties into three categories, those with less than 0.25 cars per capita, those with between 0.25 and 0.274 and those with above 0.275 car per capita, we find that they exhibit certain common features (see Figure 4.2). The low car owning group tend to be counties with substantial urban concentration.

The Central Scottish counties of Fife, Lothian, Strathclyde and

---

Central Scotland fall into this category along with the counties of South Wales. In England, the counties of Durham, Northumberland, Humberside and Derby, each with a substantial industrial component in their economies, together with the Metropolitan centres of Tyne and Wear, West Yorkshire, South Yorkshire, Greater Manchester and Merseyside, all exhibit comparatively low car ownership levels.

The second category of counties, those lightly shaded in Figure 4.2, are much more heterogeneous. Some are large centres of population, such as Greater London and the West Midlands, and others are dominated by free standing cities, such as Leicestershire,
Variations in car ownership (1978) amongst British counties

Nottinghamshire and Warwickshire. At the other extreme many of the counties are rural rather than urban by nature, notably the Scottish counties outside of the central area, the Welsh county of Clwyd and the English counties of Cumbria and North Yorkshire. Additionally,
the southern commuter areas of East Sussex and Kent fall into this central band.

The high car owning counties, those heavily shaded in Figure 4.2, tend to be located around the periphery of the country. This category, for example, embraces both the Orkney and Shetland groups of islands off North Scotland as well as the regions of East Anglia and the South West which have particularly high ownership (all component counties having per capita ownership exceeding 0.275 vehicles). A number of commuting counties for London - West Sussex, Hampshire, Surrey, Essex and Hertfordshire - also fall into the category. In general, there appears to be a lack of predominantly industrial counties in this group.

4.3 Some Statistical Modelling

This preliminary examination of the basic data confirms a pattern which was initially described by Sleeman. There is supporting evidence that similar types of area have the same general levels of car ownership irrespective of the part of the country in which they are situated. Whereas Sleeman explored these characteristics using, in the main, tabular comparisons, it seems more appropriate to adopt simple econometric tools given the likely interactive effects of some of the influences on car ownership. Buxton and Rhys adopted such an approach but concentrated their efforts on examining the influence of population density and the age distribution of the population on

ownership levels. While these factors, together with the frequently used income variable, appear important, it is also felt from the initial examination of the data that they are inadequate in themselves as an explanation of geographical variations of ownership. Further, given that the data is of much more recent origin and the ultimate saturation level of car ownership is, therefore, closer, there seems to be cause to consider whether the variables used by Buxton and Rhys, and income in particular, are still significant influences on spatial variations in ownership. Finally, recent work by the Regional Highway Traffic Model team (RHTM) suggests that more complex model specifications may be needed to reflect fully the influences exerted on car ownership. The work of McCarthy using cross-sectional and pooled Irish data would seem to confirm the inadequacy of the simple linear model.

Statistical tests of three types were performed to look at the reasons for the geographical variations in car ownership which have been observed in Great Britain. The first test involved exploring the various growth rates of car ownership found in different geographical regions. The second involved employing pooled regression techniques, while the final approach adopted a simplified logit framework. The results of each are reported in turn.

The extrapolative approach to car ownership modelling applied at the national level may also be employed in regional analysis. Much of the early work by the TRRL implicitly accepted, but never stated, the assumption that there is a single national saturation level of car ownership applicable in all regions. Kirby,\(^\text{(16)}\) while looking at national models of car ownership, found from empirical observation using logistic-curve models that for different individual regions of the United Kingdom a relationship existed between his predicted saturation level (for the region) and its current car ownership level which was superficially consistent with:

\[
\frac{S_i}{C_{it}} = \theta_t
\]

Eq. 4.1

where \(S_i\) is the saturation level of per capita car ownership in region \(i\)

\(C_{it}\) is current car ownership per capita in region \(i\)

\(\theta_t\) is a constant dependent only on time (\(t\))

In practical terms this suggests that for national forecasting one should pool the data for all the independent regions and for all time periods to obtain simultaneous estimates of the saturation levels.

15. This sub-section draws upon K.J. Button, A.S. Fowkes and A.D. Pearmain: Modelling regional and national levels of car ownership, in P.T.R.C.: Transportation Models, PTRC-SAM, 1977, pp.33-49. An earlier version of this paper appeared as, Modelling regional and national levels of car ownership, Occasional Research Paper No.11 (Department of Economics, Loughborough University), 1977. The appendix of this paper offers a more detailed mathematical argument.

There are problems with this approach, however, because if we substitute the regional logistic car ownership equation into equation 4.1 we find:
\[ \Theta_t = 1 + b_i e^{-a_i S_{it}} \]  
Eq. 4.2

This equation defines a time path for \( \Theta_t \) in terms of the parameters of the \( i^{th} \) region. As \( \Delta t \to \infty \), \( C_{it} \to S_i \), as one would expect.

Further, when \( t = 0 \), \( \Theta_0 = 1 + b_i \). If equation 4.2 is to hold for all regions, then
\[ a_i S_1 = a_i S_2 = \ldots \ldots = a_i S_i = z \]
where \( z \) is independent of time and region.

Thus equation 4.2 may be rewritten as:
\[ \Theta_t = 1 + (\Theta_0 - 1)e^{-zt} \]  
Eq. 4.3

Now, from the standard logistic growth path it may be shown that the implicit relationship between the proportional rate of growth of car ownership in region \( i \) in period \( t \) is
\[ G_{it} = \frac{a_i S_i - a_i C_{it}}{a_i S_i} = \frac{z - \frac{a_i S_i}{\Theta_t}}{z \left(1 - \frac{1}{\Theta_t}\right)} \]  
Eq. 4.4

This implies that rates of growth of car ownership are equal in all regions in any one time period. Not only does this seem intrinsically unlikely, but also, it is denied by the empirical evidence presented in Figure 4.3. If Kirby's proposition is correct
this would imply a horizontal relationship between growth rates and ownership rates for any cross-section of regions. This is manifestly not the case.

(Note: numbers under regional initials refer to persons per sq.Km. and those in brackets to conurbations percentage.)

Figure 4.3
The growth paths implied by present car ownership levels and Kirby's estimates of saturation

In an attempt to circumvent these problems and gain a better understanding of why the growth paths differ some simple calculations were performed in which the causes of the observed differences between areas were hypothesised. A simple pooling was performed employing variables designed to deal with the causes of spatial variation.

The variables used were:
PD : population density of region in persons per square mile

PC : percentage of the population living in conurbation of size greater than 250,000

(These variables are also subjected to further analysis in the following subsections.)

Initially the regional saturation levels found by Kirby(17) were regressed against the two spatial variables using data for 1970. The results obtained were:-

\[ S = 385.4 - 0.0036PD - 282.68 PC^* \]  
\[ (0.002) \quad (106.19) \]  
\[ R^2 = 0.506 \]  

*significant at the 5% level.

As one would expect the saturation level of household car ownership appears to be lower in regions which are less heavily populated and less urbanised. The level of aggregation (i.e. to the regional level) may be thought excessive, however, so further tests were performed using county level data. Rather than seek to explain the differences in saturation level, it is more convenient at the county level to look directly at the different growth rates of car ownership. Simple cross-sectional linear regression relationships between the proportional rate of growth of per capita ownership (G) were, therefore, run against the actual level of ownership for the counties of Great Britain. The figures were calculated on a year-to-year basis for the period 1966-70 and the results shown in Table 4.3.

17. loc. cit.
Years | a | b | $R^2$
--- | --- | --- | ---
1964-5 | -0.0719 | 0.7290 | 0.1485
1965-6 | 0.1220 | -0.3540 | 0.0412
1966-7 | 0.0526 | 0.1124 | 0.0175
1967-8 | 0.0362 | 0.0098 | 0.0001
1968-9 | -0.0783 | 0.4513 | 0.1721
1969-70 | 0.0217 | 0.0181 | 0.0007

(Equation from $G = a + bC$

Table 4.3

County Cross-Sectional Growth Rate Regressions

It is quite clear that the level of explanation is poor, tending to refute the theory postulated by Kirby. There is also little of consistency in the signs of the various parameters over time. Attempts to pool the county data over various time periods did nothing to improve the results.\(^{(18)}\) Following the initial hypothesis that some measure of population density might improve the quality of explanation obtained, PD and PC variables were introduced into the cross-sections. No improvements materialised. The result for the entire period (i.e. 1966-72 pooled county data) was equally poor, viz:

$$G = 0.071 + 0.0002PD - 0.11PC^* - 0.010C$$

Eq. 4.6

$$R^2 = 0.145$$

*significant at the 5% level.

18. The result for the period 1966-72 as a whole, for example, is

$$G = 0.059 - 0.080C$$

$$R^2 = 0.094$$
In summary, the application of growth model procedures at the regional level does not offer any additional insights into the spatial variations in car ownership rates nor does it seem to provide a particularly robust method of car ownership forecasting. Partial explanations for the differing regional saturation levels and growth paths are found in spatial variables and these are looked at again in more detail and in conjunction with socio-economic variates in the following sub-sections.

4.3-2 Pooled Models of Car Ownership

A number of pooling procedures are available but here the results are presented from the simple regression pooling method, dummy variable

\[ C_i = a + \sum_{i=1}^{P} b_i Y_i + U_i \]

was superior to either the dummy variable specification:

\[ C_i = a + \sum_{i=1}^{P} b_i Y_i + \sum_{t=1}^{T} b_t d_t + \sum_{r=1}^{R} b_r d_r + U_i \]

where 
\[ d_t = \begin{cases} 1 & \text{when the obs. refers to time period } t \\ 0 & \text{otherwise} \end{cases} \]

\[ d_r = \begin{cases} 1 & \text{when the obs. refers to region } r \\ 0 & \text{otherwise} \end{cases} \]

or the restricted least squares method.

Generalised least squares, i.e. using

\[ b = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}y \]

could not be used to remove serial correlation because of inadequate computer facilities. Consequently, the significance of its parameters could not be tested accurately using the usual standard error procedures.
method and restricted least-squares approach. The data employed covers nine English regions (the eight standard regions with the South East divided into the GLC area and the remainder) for the period 1965-1972 and is extracted from the Abstract of Regional Statistics, the Annual Abstract of Statistics, and the 1966 Sample Census: Economic Activity, Volume 3. A variety of socio-economic influences are combined with geographical variables in an attempt to explain variations in regional cars per household (C). Specifically the independent variable used are:

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>RLDSP</td>
<td>real household disposable income</td>
</tr>
<tr>
<td>CNPCT</td>
<td>percentage of the population living in conurbations or cities of over 250,000 inhabitants</td>
</tr>
<tr>
<td>POPDN</td>
<td>population density</td>
</tr>
<tr>
<td>UNPCT</td>
<td>percentage of the male working population unemployed</td>
</tr>
<tr>
<td>WKPCT</td>
<td>percentage of the population falling in the working age range</td>
</tr>
<tr>
<td>AGPCT</td>
<td>percentage of the male population employed in agriculture</td>
</tr>
<tr>
<td>SEG</td>
<td>percentage of the male population falling in SEG classifications 1, 2, 3, 4 and 13</td>
</tr>
<tr>
<td>T and $T^2$</td>
<td>time trends</td>
</tr>
<tr>
<td>$R_2$</td>
<td>Yorkshire and Humberside</td>
</tr>
<tr>
<td>$R_3$</td>
<td>East Midlands</td>
</tr>
<tr>
<td>$R_4$</td>
<td>East Anglia</td>
</tr>
<tr>
<td>$R_5$</td>
<td>Greater London Council Area</td>
</tr>
<tr>
<td>$R_6$</td>
<td>Rest of the South East</td>
</tr>
<tr>
<td>$R_7$</td>
<td>South West</td>
</tr>
<tr>
<td>$R_8$</td>
<td>West Midlands</td>
</tr>
<tr>
<td>$R_9$</td>
<td>North West</td>
</tr>
</tbody>
</table>
(Only eight of the nine regions are given dummies; the first region, the North, is excluded in the calculations.)

The income variable perhaps needs a little explanation. Since a car is essentially a luxury, given a lower priority in expenditure terms to both necessities and a range of semi-necessities. To reflect this, the RLDSP variable is calculated by subtracting from the total personal incomes per household (after tax and deductions) a Family Expenditure Survey based estimate of expenditure on housing, fuel and food, the whole being weighted by a retail price index. It is also worth noting that RLDSP is in effect a lagged variable since income for, say, 1965 is based upon tax returns for the financial year 1964-5. The socio-economic variables (SEG, UNPCT, WKPCT and AGPCT) are intended to represent both the differing needs of groups within society and the various 'tastes' of households with different socio-economic characteristics. The population density and urbanisation measures are seen as alternative proxies for the quality of local transport provision - both the greater congestion found in heavily populated areas and the availability of adequate public transport normally associated with urban areas (see section 3.3-3 below).

Table 4.4 gives the main results for the alternative pooled models which were fitted - in some cases double log transformations were also fitted and the results are also given. The simple pooling models (equations 4.7 - 4.14) make no allowance for regional differences. All specifications provide a high degree of explanation of the variation in the dependent variable although the double log
<table>
<thead>
<tr>
<th>Equation</th>
<th>4.7</th>
<th>4.8</th>
<th>4.9</th>
<th>4.10</th>
<th>4.11</th>
<th>4.12</th>
<th>4.13</th>
<th>4.14†</th>
<th>4.15</th>
<th>4.16</th>
<th>4.17</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable</td>
<td>C</td>
<td>C</td>
<td>C</td>
<td>C</td>
<td>C</td>
<td>C</td>
<td>C</td>
<td>C</td>
<td>C</td>
<td>C</td>
<td>C</td>
</tr>
<tr>
<td>Constant</td>
<td>0.329</td>
<td>0.028</td>
<td>0.305</td>
<td>0.294</td>
<td>0.468</td>
<td>0.278</td>
<td>0.439</td>
<td>15.090</td>
<td>0.236</td>
<td>0.130</td>
<td>0.508</td>
</tr>
<tr>
<td>RLDSP</td>
<td>0.008*</td>
<td>0.0004*</td>
<td>0.0008*</td>
<td>0.0004*</td>
<td>0.0004*</td>
<td>0.0004*</td>
<td>0.0004*</td>
<td>0.0004*</td>
<td>0.0002</td>
<td>0.0004</td>
<td></td>
</tr>
<tr>
<td>AGPCT</td>
<td>0.007</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WKPCT</td>
<td>-0.004*</td>
<td>-0.003*</td>
<td>-0.004*</td>
<td>-0.003*</td>
<td>-0.002*</td>
<td>-0.016*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CNPCT</td>
<td>-0.034*</td>
<td>-0.034*</td>
<td>-0.035*</td>
<td>-0.035*</td>
<td>-0.037*</td>
<td>-0.016*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UNPCT</td>
<td>-0.002*</td>
<td>-0.002*</td>
<td>-0.002*</td>
<td>-0.002*</td>
<td>-0.002*</td>
<td>-0.002*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SEG</td>
<td>0.017</td>
<td>0.012*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>POPDN</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T</td>
<td>0.003</td>
<td>0.042*</td>
<td>0.017</td>
<td>0.026</td>
<td>0.041*</td>
<td>0.0407*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T²</td>
<td></td>
<td>0.00004</td>
<td>0.001</td>
<td>0.002</td>
<td>0.004</td>
<td>0.004</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>71.1</td>
<td>77.9</td>
<td>71.3</td>
<td>71.5</td>
<td>78.3</td>
<td>52.4</td>
<td>78.6</td>
<td>46.9</td>
<td>93.12</td>
<td>97.28</td>
<td></td>
</tr>
</tbody>
</table>

*Parameter significant at the 5% level
†Variables all expressed as logarithms to base e.

Table 4.4
Pooled Regression Results
specification (equation 4.14) is seen to be less satisfactory than a simple linear model. (20) It is also seen that most of the regression parameters take signs consistent with a priori expectations. (21) Visual inspection of the residual variation, however, shows that in all cases car ownership is consistently over-predicted in some regions and under-predicted in others. There is, in other words, spatial auto-correlation. In view of the fact that the logarithm transformation did not reduce the amount of this over and under prediction, it seems quite probable that variable omission is the root of the problem.

Since there seems to be a marked difference between regions in the first set of results, dummy variables are introduced to differentiate between regions. In this analysis only shift dummies are employed and some of the results are seen in Table 4.2, equations 4.15 and 4.16. While this modification obviously improves the fit (i.e. $R^2$) of the model and reduces the auto-correlation problem, the effect on the significance and signs of the primary explanatory variables are deleterious.

Figure 4.4(a) plots the residuals for equation 4.7 and the over-predictions for the North, Yorkshire/Humberside, East Midlands and North West are clear. In Figure 4.4(b) a simpler dummy variable specification than that used in the body of the text is applied with

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20. This runs counter to several earlier studies. See, for example, Buxton and Rhys, op. cit., and Sleeman (1969), op. cit.

21. For an interesting comparison of the income parameter obtained in these models with a more conventional income variable, see Chapter 6.
\[ C = 0.329 + 0.008RLDSP - 0.004CNPCT + 0.003T^2 \]

\[ C = 0.334 + 0.0001RLDSP - 0.005CNPCT + 0.023T^2 + 0.232D_1 + 0.132D_2 \]

(a)  
(b)  

Figure 4.4

Plots of residuals from selected pooled regressions

dummies \( D_1 \) for regions East Anglia, South West and the Rest of the South East and \( D_2 \) for regions East Midlands, West Midlands and Greater London.\(^{22}\) It is clear from simple observation that the auto-correlation problem is considerably reduced by this expediency - the use of individual dummy variables as in equations 4.15 and 4.16 reduces it further.

\(^{22}\) For further details of these calculations see K.J. Button and A.D. Pearman: The theory and practice of car ownership forecasting in E.J. Visser (ed.): Transport Decisions in An Age of Uncertainty (Martinus Nijhoff, the Hague), 1977, pp.137-144.
The third approach involves the use of a two-stage restricted least squares application with county level data from the 1966 sample census used to determine the SEG, UNPCT and CNPCT parameters. Using such parameters the residual difference between actual and predicted car ownership rates at the regional level was then regressed against T. By combining the parameters so derived from the two regressions, an alternative estimating equation for car ownership per household is obtained - equation 4.17. The signs of the independent variables are logical and significant and compare favourably with the results of the dummy variable specifications. Car ownership in equation 4.17 appears to decline more rapidly with the rate of male unemployment and increase more rapidly with the proportion of the population in the selected Social Economic Groups than with the other models.

Overall the empirical results obtained by pooling offer some improvement on the simple cross-sectional or time series models which have gone before. The real disposable income parameter has frequently proved both positive and significant, which was not always the case in earlier work (see below). The values attached to this parameter in the equations suggest an income elasticity of about 0.5 which is much lower than that found in earlier studies. This may, in part, be a reflection of the form of variable employed as well as being a consequence of pooling. Furthermore, the parameter relating to the percentage of each region's population living in conurbations or large cities is also consistently significant. Its negative sign reflects, it is thought, the superior public transport systems and general ready access within such areas. The pooled study also seems to indicate
that local unemployment may have some bearing on car ownership.

4.3-3 Cross-Sectional Logit Models of Car Ownership

The data employed is taken for two years, 1976 and 1978, so that short term comparisons can be made in addition to longer term ones with Buxton and Rhys. Linear and log-linear specifications are employed but in addition the logit formulation favoured by the RHTM is also tested. The basic logit equation form is:

\[ C_i = \frac{S}{1 + e^{x + \sum_j b_j x_{ij} + u_{ij}}} \]

where \( C_i \) is cars per capita in county \( i \)
\( S \) is the asymptote
\( x_{ij} \) is an explanatory variable
\( u_{ij} \) is a random disturbance.

For calibration purposes this may be simplified to:

\[ \ln \left( \frac{S}{C_i} - 1 \right) = \alpha + \sum_j b_j x_{ij} + u_{ij} \]

which, if a predetermined value of \( S \) is substituted, may be estimated using ordinary least-squares. Since \( S \) is the asymptote it represents the ultimate saturation level of car ownership. As we saw in Chapter 4 a number of definitions of the saturation level exists but here the

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23. Buxton and Rhys, op. cit.

concept is being employed in a purely mechanical sense. It is being treated as a parameter without any attempt being made to either offer a detailed interpretation or to give an exact evaluation.

Although the value of $S$ is obviously not known, a number of studies have suggested that a figure of around 0.40 to 0.45 cars per capita may be a reasonable approximation. This is, for example, the order of magnitude often used in aggregate national car ownership forecasting exercises by the Transport and Road Research Laboratory. (25)

The independent variables examined in this simple econometric analysis are:

**Y**: Male Earnings. This was taken from the New Earnings Survey and is employed as a proxy for income. Intuitively one would anticipate counties with higher earnings to exhibit, *ceteris paribus*, high levels of car ownership.

**P**: Population Density. This is a frequently used variable which, it is claimed, acts as a proxy for accessibility. High population density usually means easy access to places of work and recreation both because of geographical proximity and good public transport. One would anticipate that this ease of access combined with the congestion of private transport found on roads in densely populated areas would discourage high levels of car ownership.

---

R : Rateable Value of Property. This variable is not strictly comparable between Scotland and the rest of Great Britain. The valuations were independently undertaken, for Scotland this was in 1971 and for the remainder of the country 1973. Since this variable gives some indication of the wealth of a country it is, a priori, anticipated that it would be positively correlated with car ownership.

E : Unemployment Rate. This figure, extracted from the Department of Employment Gazette, is intended as a social proxy to reflect the general economic prosperity of counties. One would anticipate a negative correlation with car ownership.

A : Percentage of Employees Employed in Agriculture. This is intended to supplement the population density variable as a guide to the geographical nature of a region. The generally poor public transport associated with rural areas would suggest a positive correlation between the degree of ruralisation of a county and per capita car ownership.

The results of these regressions are presented in Table 4.5 for both 1976 and 1978. The table shows both the parameters obtained when using the full set of variables in each model and also the 'best' fitting models when highly insignificant or collinear variables are omitted. The simple statistical tests of fit were performed and an indication of both the overall explanation ($R^2$) and the general significance of separate independent variables is shown. Equations 4.24, 4.25, 4.29 and 4.31, which have a logit specification, have been calculated assuming $S = 0.40$. This value seems to offer the highest
### Table 4.5

Values of $b_j$ for Various Specifications of the Simple Car Ownership Model (1976 and 1978)

<table>
<thead>
<tr>
<th>Equation No.</th>
<th>Dependent Variable</th>
<th>1976</th>
<th>1978</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Intercept</td>
<td>Y</td>
</tr>
<tr>
<td>4.20</td>
<td>C</td>
<td>0.446</td>
<td>-0.0031*</td>
</tr>
<tr>
<td>4.21</td>
<td>C</td>
<td>0.231</td>
<td>0.00037*</td>
</tr>
<tr>
<td>4.22</td>
<td>ln C</td>
<td>0.240</td>
<td>-2.493</td>
</tr>
<tr>
<td>4.23</td>
<td>ln C</td>
<td>-2.06</td>
<td>0.0327*</td>
</tr>
<tr>
<td>4.24</td>
<td>logit C</td>
<td>-2.06</td>
<td>0.0327*</td>
</tr>
<tr>
<td>4.25</td>
<td>logit C</td>
<td>0.207</td>
<td>-0.0059*</td>
</tr>
</tbody>
</table>

| 4.26         | C                  | 0.190 | -0.0002 | -0.00001* | 0.0005* | -0.0022 | -0.0068* |
| 4.27         | C                  | 0.154 | -0.00001* | 0.0006* | 0.0070* | 0.1447 | 0.0222 | 0.1740* | -0.0148* | 0.1168* | 0.604 |
| 4.28         | ln C              | -2.841 | -0.00001* | 0.0006* | 0.0070* | 0.1447 | 0.0222 | 0.1740* | -0.0148* | 0.1168* | 0.604 |
| 4.29         | ln C              | -2.194 | -0.00001* | 0.0006* | 0.0070* | 0.1447 | 0.0222 | 0.1740* | -0.0148* | 0.1168* | 0.604 |
| 4.30         | logit C           | 0.421 | -0.0008 | 0.00014* | -0.0064* | 0.0233 | -0.0785* |
| 4.31         | logit C           | 0.580 | 0.00015* | -0.0068* | -0.0795* |

(1) * significant at the 5% level
+ significant at the 10% level

(ii) The regressions are based upon 64 observations.

(iii) logit C indicates the transformation $\ln \left( \frac{C}{C - 1} \right)$. 


values of $R^2$ for the equations but, after testing with alternative values, the impression gained is that the model is fairly insensitive to the saturation level within the range $S = 0.35$ to $0.50$.

The most immediately apparent fact is that income tends frequently to take a perverse sign - one that would not be anticipated from basic economic theory - and does not prove to exert a particularly significant influence on car ownership in many of the equations. (Intuitively one would anticipate a positive correlation to exist between income and car ownership in the case of the linear and log-linear specifications, and because of the reciprocal form of the dependent variable, a negative correlation to appear in the logit model.) One reason for this perverse finding may be that earnings are a poor proxy for income, another is that the New Earnings Survey is in itself deficient. Attempts to assess the validity of using earnings rather than income at the standard region level of aggregation did little to clarify the matter. Using 1978 regional data, household income did exhibit a positive relationship with car ownership but it was extremely weak ($t = 0.61$). At the same level of aggregation, the earnings variable again proved negative and very insignificant.

Although both of the points made above may be valid criticisms of the use of an earnings variable, there is also the possibility that income does not exert a systematic effect on geographical variations in British car ownership patterns. This suggestion, in
fact, is not new. Sleeman\(^{(26)}\), for example, found the relationship between private car ownership and personal income (based on the Inland Revenue Reports of 1949-50) to be positive but insignificant for English and Scottish counties, and negative and insignificant for Welsh counties. Fishwick\(^{(27)}\) also found personal income to be insignificant when examining county variations in ownership and partly explained this in terms of the lagged nature of the variable. (However, when regressions were run on the 1978 county data using earnings lagged by two years as one explanatory variable this neither improved the statistical fit of the model nor changed the sign of the relevant coefficient.) Buxton and Rhys\(^{(28)}\) found income did not always appear significant when attempting to explain car ownership patterns in Wales. Sanghi\(^{(29)}\) using U.S. data for 1970, found income to be totally insignificant. As we saw in Chapter 2 (p.62) Bos\(^{(30)}\) could find no evidence of correlation between car ownership and income in the Netherlands.

A possibility is that income (or earnings) may be a relevant influence on car ownership but that standard definitions of the

\[ \text{Less Urbanised Regions: } \log C = a + 1.76 \log Y + 0.02 \log PD \\
\text{(0.45) (0.03)} \\
\text{More Urbanised Regions: } \log C = a + 2.89 \log Y - 0.10 \log PD \\
\text{(0.96) (0.10)} \\
\]

No Chow tests were performed to test the validity of the less urban/more urban dichotomy.

26. Sleeman (1958), \textit{op. cit.} In his later work, however, Sleeman (1969), \textit{op. cit.}, found that for 1966 income had become a significant variable in his regression analysis, specifically

\[ \text{Less Urbanised Regions: } \log C = a + 1.76 \log Y + 0.02 \log PD \\
\text{(0.45) (0.03)} \\
\text{More Urbanised Regions: } \log C = a + 2.89 \log Y - 0.10 \log PD \\
\text{(0.96) (0.10)} \\
\]


28. Buxton and Rhys, \textit{op. cit.}

29. Sanghi, \textit{op. cit.}

variable may be inappropriate. In time series studies, allowance has been made for changes in the 'car purchasing' value of income (31) and also some cross-sectional work has attempted to allow for spatial variations in prior demands on income (e.g. housing, food, etc.) The first of these is really inappropriate in cross-sectional work while the second introduces an excessive degree of arbitrariness into the analysis. (32) Another economic explanation, drawn from macro-economics, is that only 'permanent', rather than current income, influences the consumption of, in this case, cars. Current income, according to this theory, often contains elements of 'transitory' income which do not influence purchasing decisions.

Statistically, if earnings do contain an excessive element of transitory income this would imply that the models tested (i.e. equations 4.20 and 4.31) using ordinary least squares suffer from error in variable problems. More specifically, the standard regression assumptions are violated because the measurement errors in earnings are greater than those in car ownership. If this is so then some notion of the possible errors resulting can be obtained by running models with Y or In Y as the dependent variable and C, In C or In \( \left( \frac{S}{C} - 1 \right) \) as an independent variable and then re-arranging them with car ownership, or the appropriate logit, on the left-hand side. Some results of doing this are given as equations 4.32 - 4.35 in Table 4.6. Generally the negative earnings effect remains and, in addition, the fit of the models is much lower than comparable specifi-

31. Bates et al., op. cit.

cations in Table 4.5. Differences between permanent and transitory incomes therefore do not seem important nor to operate consistently against each other.

<table>
<thead>
<tr>
<th>Equation No.</th>
<th>Dependent Variable</th>
<th>Intercept</th>
<th>Y</th>
<th>P</th>
<th>R</th>
<th>E</th>
<th>A</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.32</td>
<td>C</td>
<td>2.801</td>
<td>-0.0365</td>
<td>0.00003</td>
<td>0.0004</td>
<td>-0.0058</td>
<td>-0.0164</td>
<td>0.300</td>
</tr>
<tr>
<td>4.33</td>
<td>logit C</td>
<td>-1.758</td>
<td>0.2526</td>
<td>-0.0002</td>
<td>-0.0630</td>
<td>0.0433</td>
<td>0.0680</td>
<td>0.334</td>
</tr>
<tr>
<td>4.34</td>
<td>C</td>
<td>17.666</td>
<td>-0.2140</td>
<td>0.0003</td>
<td>-0.0013</td>
<td>-0.1226</td>
<td>-0.1047</td>
<td>0.282</td>
</tr>
<tr>
<td>4.35</td>
<td>logit C</td>
<td>637.3</td>
<td>-7.7760</td>
<td>0.0147</td>
<td>-0.0762</td>
<td>-4.3561</td>
<td>-4.1321</td>
<td>0.281</td>
</tr>
</tbody>
</table>

Table 4.6

Given the general nature of the results, are there any theoretical reasons why geographical differences in car ownership need not be a positive function of income? The answer possibly lies in the nature of the influences at work on car ownership; some are essentially constraints while others act as a direct inducement to own a car. Heggie(33) suggests that while much of the standard literature treats income as a causal variable, it is in fact one of a series of constraints limiting ownership. A household is seen as a potential car owning unit only when a threshold income level has been exceeded. It could well be that, with the general upward movement in income and the growth of car ownership towards the ultimate national saturation

level over the last twenty-five years, this constraint is not so
binding and hence appears insignificant in this and other work.
If the explanation is of this nature, however, then one would also
anticipate that income growth over recent years would have ceased
to exert a positive influence over the aggregate level of national
ownership. There is, however, no evidence of this from time
series studies. In addition, many of the other studies which found
income to be a poor explanatory variable in cross-sectional work -
e.g. Sleeman \(^{(34)}\) - were carried out well before the saturation level
began to be approached.

An adaptation of the constraint theory seems necessary and, in
particular, it is important that cognisance be taken of the complexity
of the car market. There is a tendency for much of the thinking on
geographical car ownership distribution at the regional level to be
dominated by the demand aspects to the neglect of supply. (An
exception being the work of Mogridge. \(^{(35)}\)) The complexity of new
and secondhand car markets combined, almost by definition, with the
mobility of the product means that regional income differentials are
likely to be offset to a considerable degree by adjustments in local
supply conditions. Hence, although income may be a constraint which
is relaxed as its level increases, it does not have an important spatial
effect any any one point in time. A wealthier region will, \textit{ceteris
paribus}, simply have a better, possibly newer, stock of cars than a
poorer one.

34. Sleeman (1958), \textit{op. cit.}
Economics and Policy}, Vol.1, 1967, pp.52-73, and, A personal view on
the future of the car, \textit{Traffic Engineering and Control}, Vol.17,
An additional factor likely to have negated the effect of income on the distribution of vehicle ownership in our calculations is the rapid rise in financial assistance offered by employers towards the costs of owning and running a car. In 1971 the Motor Transactions Survey showed 56 per cent of new cars were purchased entirely or partly for business use, but this contrasts with the lower figure of 31 per cent which was accepted by the Inland Revenue for taxation purposes. The British Institute of Management\(^{(36)}\) have estimated, from a survey of 471 firms, that over 70 per cent of new car sales in 1978 were, in fact, to company fleets rather than private individuals. It is clear that a company car is now often taken in preference to income. Additional to this, and despite legislation to tighten up on tax avoidance, many older cars are also still, to some degree or another, indirectly financed by firms (e.g. by giving generous mileage allowances). It is not possible to make systematic allowances for any spatially differential effects induced by subsidies of this kind but they are playing an increasing part in deciding ownership patterns and are clearly exerting an influence directly counter to that of any income effect.

A much more important influence on vehicle ownership than income seems, from the equations, to be exerted by both the geographical variables (population density and agricultural employment) and the rateable value of property variable. The latter may be seen as a proxy for wealth although it exhibits little correlation with the

earnings variable - the zero correlation coefficients for 1976 and 1978 being 0.229 and 0.213 respectively. If it does reflect the general prosperity of a region then this would suggest that forms of financial income other than earnings are important in influencing car ownership levels. This may not be unreasonable if during the years considered employees were, as suggested in the previous paragraph, obtaining indirect financial support for their vehicles, not reflected in earnings, which have permitted them to enjoy a higher real standard of living.

The high level of significance attached to the population density and agricultural employment variables combined with their associated signs supports the hypothesis that areas likely to have poor public transport provision, rising levels of traffic congestion and where longer journeys are required for work and recreational purposes, have high car ownership levels. This confirms the findings of a number of other studies, where spatial variables of this type have been adopted. The population density elasticity, in particular, exhibits values of down to -0.47 which corresponds well with the -0.2 to -0.5 range found by McCarthy (37) for Ireland although they are somewhat lower than the -0.09 to -0.11 estimated to apply in England and Wales by Rhys and Buxton. (38) These findings emphasise the sensitivity of car ownership to local transport conditions; a fact of importance to transport policy-makers given the relative fuel efficiency of alternative modes of transport.

37. McCarthy, op. cit.

38. Rhys and Buxton, op. cit.
The unemployment variable is also observed to be significant in several of the equations with signs suggesting an inverse relationship with car ownership. One explanation of this could be that unemployment is highly correlated with earnings and is, therefore, soaking up much of the impact of the earnings variable. Examination of the intercorrelation matrix, however, reveals a relatively low level of correlation (the zero-order coefficients being -0.0018 and -0.14 respectively for 1976 and 1978). A more probable explanation of the significance and sign of the unemployment variable is that car ownership decisions are related to the requirements of workers to reach their place of employment. Areas with relatively high levels of unemployment will, therefore, have lower than average levels of car ownership. Employment, thus, seems to be one of the positive inducements which Heggie\textsuperscript{(39)} argues acts to encourage car ownership.

In general the results confirm the gradually evolving view that the linear and log-linear models favoured by Sleeman, Buxton and Rhys and others are less satisfactory than the adoption of some form of sigmoid transformation. Although the symmetrical form of the logit relationship used here does not necessarily offer the best statistical fit of the alternative sigmoid formulations available (for example, a non-symmetrical specification may prove superior), it does provide a simple, quick, and for planning purposes, practical method of data fitting (via the linear transformation). Further, from an economic viewpoint, it can be justified, making reasonable

\footnote{39. Heggie, \textit{op. cit.}}
assumptions, in utility theory.\textsuperscript{(40)} The difficulty with the logit is the specification of an independently determined saturation level to act as the asymptote although, in practice, major problems may be circumvented by using a series of simple iterative calculations taking different values of saturation.

4.4 Conclusions

The general conclusion is that the situation with regard to geographical variations in car ownership in Great Britain has changed little over the past twenty-five years. There is, however, some evidence that the geographical distribution of ownership is extremely sensitive to direct geographical variables, acting as proxies for the general quality of transport and access in an area. This suggests that car ownership patterns may be influenced by transport and land-use policies (a subject explored in more detail in the following chapter) and should not, as has been the case in Great Britain until comparatively recently, be treated as exogenous inputs into transport planning policies.\textsuperscript{(41)} Income, however, plays a much less direct, but more complex, role in explaining regional geographical variations in vehicle ownership than many earlier studies have suggested. The emphasis on the effect income has on the spatial demand for cars ignores the diverse nature of the spatial supply of vehicles, hence

\textsuperscript{40} L.D. Burns, T.F. Golob and G.C. Nicolaides: Theory of urban household automobile-ownership decisions, Transportation Research Record No.569, 1975, pp.56-75.

\textsuperscript{41} For a further discussion see also K.J. Button and A.D. Pearman: An economic analysis of local geographical variations in the level of car ownership, Paper Presented at the Association of University Teachers of Economics Conference, 1981.
an area with low income can still enjoy a high ownership level if
the general quality of vehicles is also relatively low. Further,
and because the growth path is now well past the point of inflection,
the study confirms that the simple linear and log-linear relationships
observed a decade ago are inappropriate specifications of the under-
lying causal form of recent trends. It seems that we are now reaching
the stage where a levelling off in the growth of car ownership in some
areas can be anticipated and, therefore, given the variations in growth
between counties, a sigmoid model seems to provide a superior frame-
work of analysis.
CHAPTER 5

DISAGGREGATE MODELLING OF LOCAL GEOGRAPHICAL VARIATIONS
IN TRIP GENERATION AND THE LEVEL OF CAR OWNERSHIP(1)

5.1 Introduction to Disaggregate Modelling

The rapid rise in car ownership during the post-war period has posed serious problems for urban policy-makers. The difficulties arise not from car ownership itself, but as a consequence of the observed relationship between the level of ownership and total car use. (2) Increased levels of car traffic do not simply result in strains being placed on the local transport system—causing congestion on the road network and creating financial problems for underutilised public transport services—but also impose severe environmental costs on local residents. In the longer term, the increased mobility afforded by car ownership influences land-use


2. While this relationship was generally accepted until the mid-1970s, reaction to the fuel crisis of 1974 suggests that car use cannot simply be related to the number of cars and the size of the road system, as was previously the case. The Leitch Committee (Department of Transport:- Report of the Advisory Committee on Trunk Road Assessment (HMSO, London), 1978), therefore, suggested the introduction of a more sophisticated forecasting technique at the national and inter-urban levels.

190.
patterns and there is ample evidence to relate the growth in suburban living to higher levels of vehicle ownership.

Given these circumstances, it is not surprising that there is a growing interest both in explaining the existing patterns of urban car ownership and in attempting to forecast their development. This interest, particularly in the United Kingdom, has grown up rather slowly, especially when set beside the work carried out on national car ownership forecasting and on the demand for new cars. As we see below, the recent upsurge in interest in urban car ownership modelling may, in part, be attributable to developments in urban transport planning methodology, but it must also be related to institutional changes whereby local authorities have, since 1975, to submit Transport Policy and Programme (TPP) statements to obtain central government funds. The preparation of TPPs has focused attention on some of the deficiencies in our knowledge of how the urban transport market functions.

Financial restrictions have also both changed the emphasis in transport planning (away from consideration of large investment programmes towards smaller scale changes designed to bring about the more efficient utilisation of existing transport resources) and also placed constraints on the funds available for data collection. Rapid advances in computer technology now make it possible to calibrate much complex models both quickly and cheaply. Hence there have been pressures to make better use of smaller data sets. Additionally, as was seen in Chapter 1, travel is no longer viewed as a simple,

3. See Chapter 3 for details.
almost mechanistic process, but is now recognised to be subject to a large range of socio-economic influences. Complementary to this, the idea of essentially determinist modelling - where attempts are made to forecast, say, the number of trips by mode m from origin i - has given way to a more stochastically orientated approach - whereby the probability of a traveller choosing mode m for travel from origin i is considered.

Disaggregate travel demand models are concerned with discrete choices made by households (or individuals) - e.g. as to whether to make a trip or not - rather than with averages of trips across households. The focus on the micro-unit does not simply conform more closely with notions of behavioural theory but, because of the lack of aggregation, permits analysis based on a considerably reduced data base. Watson(4) using a common set of variables extracted from a single data base, demonstrated that the probabilistic results obtained from a recursive model of mode choice calibrated at the level of the individual traveller give a much lower predictive error than those from a comparable deterministic model based upon geographical zones.

This change in emphasis in urban transport modelling has been slow to be accepted in Britain, particularly outside the academic

4. These claimed economies of disaggregate modelling have, however, recently been questioned by J.J. Bates:- Sample size and grouping in the estimation of disaggregate models - a simple case. Transportation, Vol.8, 1979, pp.347-369.
community. There are clearly practical problems with it which are still to be resolved satisfactorily - the most commented upon being the difficulty of aggregating household choices so that total travel by route and mode can be determined\(^6\) - but a more difficult problem is the greater complexity of the models involved and the type of data input required. Aggregate models of travel demand have often forecast trip-end rates and modal split using fairly simple models of car ownership. The latter were often little more than crude adaptations of national extrapolative forecasts modified, in some way, to allow for local circumstances. The second generation of urban traffic models require rather more sophisticated models of local car ownership which both explain geographical variations in ownership levels and the sensitivity of ownership to changes in local transport policy. Average rates of household ownership must also give way to probabilistic forecasts of no-car and multi-car households since these divisions exert important influences on travel behaviour.

Traditionally, local car ownership modelling in Britain has been based on the 'logistic curve fitting technique' developed by the Transport and Road Research Laboratory to forecast the growth of the nation's total car stock.\(^7\) While the technique conforms broadly with a product life cycle theory it is, nevertheless, essentially an extrapolative technique, primarily justified on grounds of goodness of statistical fit. Despite recent innovations, which have included

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both changes in functional form and the introduction of income and cost of motoring variables, time is still seen as the dominant influence on the growth of car ownership. Use of this type of model for local transport demand analysis has met with considerable criticism. Its very nature makes it of little use as a component of a disaggregate local transport demand modelling exercise, although it may still have a useful role to play in guiding national transport policy formulation.

A number of other aggregate studies, both cross-sectional and time series, have also been conducted, frequently to explore the regional variations in vehicle ownership which exist. Cross-sectional aggregation at the regional level obscures the effects of many variables. Collinearity also poses difficulties in the use of cross-sectional aggregate data because of the tendency for many relevant variables to change in conjunction across the country. Aggregate time series studies, which have been more frequently undertaken in the United States, often suffer from short data runs and, where data is stretched by using quarterly observations, they tend to be swamped by essentially random short-term effects, submerging the influence of longer term factors. A car is a durable good and ownership decisions tend to be based on trends in income and prices rather than short-term movements such as the irregular (often annual) jumps in prices that occur in the new car market.

The majority of aggregate car ownership models also exclude two other important influences which affect car ownership decisions.\(^{(9)}\)

Firstly, they do not normally consider the main motive for car ownership; namely, the improved access that private transport offers to a wide range of employment and social opportunities. Lip service is sometimes paid to the fact that residents of areas with poor public transport will, \textit{ceteris paribus}, be more likely to own a car than residents of areas with good public transport.\(^{(10)}\) The derived nature of the demand for car ownership, however, tends to be inadequately considered in most studies. Secondly, the differing natures of families are either ignored or characterised rather inadequately in the form of average membership. There is, however, ample evidence that stage in the life-cycle and family composition both influence travel behaviour and, \textit{ipso facto}, seem certain to exercise a considerable influence over whether a household will become car owning or not.\(^{(11)}\)

The recent work by the Regional Highway Traffic Model team,\(^{(12)}\) using Family Expenditure Survey data, constructed a household model of car ownership for national transport policy formulation purposes.

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11. See, for instance, J.D. Downes:-- Life-cycle changes in household structure and travel characteristics, \textit{Transport and Road Research Laboratory Report} 930, 1980.

This model, however, although emphasising the importance of local circumstances at the regional level, concentrates almost exclusively on the relative influences of income and car prices on household car ownership decisions to the exclusion of other socio-economic variables. It is by nature a disaggregate model but, by design, is more suited to national or regional forecasting than as a tool in local, urban transport policy formulation.

Those studies which have attempted to develop disaggregate local models of car ownership have tended to be American. Johnson (13) constructed a model based upon two sets of household data but limited his explanatory variables to income, family size and the age of the head of household - no attempt to incorporate a measure of accessibility to opportunities was made. In contrast, Burns and Golob, (14) in a model later calibrated by Burns, Golob and Nicolaidis, did incorporate an accessibility variable in addition to household income but made only a modest attempt to allow for household structure. Joint choice models have also been developed looking at, for example, household decisions regarding car ownership and mode choice (16) and location, housing, vehicle ownership and mode to work. (17) The standard

approach in these studies was the construction and calibration of multinomial logit choice models using relatively small data sets extracted from urban transport surveys.

5.2 A Disaggregate Model

This section follows in the first instance the pattern set in much of the recent American work. It uses cross-sectional disaggregate modelling techniques to look in particular at the effects of household structure and public transport accessibility on the geographical spread of car ownership in urban areas. Public transport policy is currently under review in this country and it seems appropriate to see what role, if any, it might have in containing the growth in urban car ownership and use. Differing institutional factors combined with contrasting urban forms mean that the American work in this field is likely to be of less relevance in the British context. British cities tend not to conform to the standard American grid pattern and the overall level of car ownership lags well behind that of the United States.

The underlying model is derivable from simple utility theory. We assume that a household's total utility is dependent upon the consumption of all goods, available leisure time and travel to all destinations accessible to the household within a given maximum amount of time. We define the utility enjoyed by a non-car owning household as:

\[ U_0 = U(y, T - \sum_{j \in D_0} t_{ij}, x_i) \]  

Eq. 5.1
where $U_0$ is utility without a car
y is total disposable family income
T is available leisure time
t$_j$ is travel time to destination $j$ by alternative
(i.e. non-car) modes of transport
X$_j$ is the number of trips made by the alternative modes
to destination $j$,
and $D_0$ is the set of all destinations accessible by the
alternative modes of transport.

For simplicity, we consider the alternative to having no car to
be that the household owns exactly one car. The empirical work
described later does not make this assumption, and the extension of
the theory to incorporate multiple car ownership is quite straight-
forward. Car ownership affects the household in three main ways.
Firstly, it changes, and probably increases, the range of destinations
open to the household (i.e. $D_1 > D_0$). Secondly, household income
(and, ipso facto, the consumption of other goods) is reduced by the
annual cost of running a car. Thirdly, the number of trips made to
existing destinations is likely to change. Hence, the utility
enjoyed by a household owning one car may be represented as:-

$$U_1 = U(y - p, T - \sum_{j \in D_1} s_j Z_j, Z_j)$$

Eq. 5.2

where $U_1$ is the utility with a car
p is the annual cost of car ownership to the household
in excess of the cost by the alternative mode
(assumed independent of the number of trips)
Z$_j$ is the number of trips made to destination j
$s_j$ is travel time to destination $j$ by car.
It is implied that car-owning households make a negligible number of non-car journeys. Consequently a household will move from having no car to one car when:-(18)

\[ U(y,T - \sum_{j \in D_0} c_j X_j, X_j) < U(y-p, T - \sum_{j \in D_1} p_j Z_j, Z_j) \]  

Eq. 5.3

We can see from this that the probability of car ownership is likely to be dependent upon the tastes of the household, its level of income, the relative costs of different modes of transport and the household's trip making preferences. Accessibility, in terms of transport costs, is therefore made explicit in this approach.

Application of the model requires the specification of functional forms for the utilities and, to facilitate ease of calibration, the introduction of proxy variables. (19) Following established practice in discrete transport choice modelling a logit formulation is adopted, although the method of calibration and specification follows that developed by Bates, Gunn and Roberts (20) in the United Kingdom, rather than the multinomial logit approach used, for example, by Train, (21) in America. The basis for the choice of the multinomial logit formulation is the following.

Equations 5.1 - 5.3 do not take into account the possibility of taste and perception variations, nor do they allow for the possibility that

18. This framework can not only be extended to distinguish between single- and multi-car owning decisions but also between broad types of car.


data inadequacies may forbid the explicit incorporation of all the influences into the utility functions which would be desirable from a theoretical point of view. Hence, in practice, the values of $U_0$ and $U_1$ will be random variables across samples of households.

Suppose $\epsilon_0$ and $\epsilon_1$ represent unobserved random errors, subsuming excluded decision factors and individual differences. Then random utility functions may be defined as:

$$RU_0 = f(U_0, \epsilon_0) = U_0 + \epsilon_0$$
$$RU_1 = f(U_1, \epsilon_1) = U_1 + \epsilon_1$$

if it is assumed that, by suitable scaling, they may be regarded as having an additive form.

Thus the probability that an individual household finds car ownership advantageous can be represented as

$$P_1 = \text{Prob}[U_0 + \epsilon_0 < U_1 + \epsilon_1]$$

Eq. 5.5

If it is now assumed that the $\epsilon$'s are distributed independently as a reciprocal exponential distribution, then it is straightforward\(^{(22)}\) to demonstrate that

$$P_1 = \frac{1}{1 + e^{(U_0 - U_1)}}$$

Eq. 5.6

Equation 5.6 is the standard binary logit model and can be generalised to the conditional or multinomial logit model.\(^{(23)}\)

---


logit model has proved markedly robust in a wide range of economic applications, particularly in the transport field, because it overcomes what McFadden (24) terms the "fallacy of composition" which occurs in attempting to infer response elasticities from data on behaviour of heterogeneous groups. The large data base for West Yorkshire used for empirical work in the next section permits rather more straightforward calibration than is often the case with small-sample American studies.

In this case the probability of a particular household \( i \) being car-owning is thus defined as:

\[
P_i(1+) = \frac{S(1+)}{a + b \log Y_i} + v_i
\]

\[
1 + e
\]

where \( P_i(1+) \) is the probability of household \( i \) owning at least one car

\( S(1+) \) is the saturation level of \( P(1+) \), that is, the probability of car ownership as incomes become infinitely large

\( Y_i \) is the income of the \( i^{th} \) household

\( v_i \) is a random error term

\( a \) and \( b \) are the estimated parameters, where \( b \) should be negative.

Equation 5.7 results from a particular assumption about the functional form of the utilities, which, as with the choice of the reciprocal exponential distribution for the \( \epsilon \)'s, is made with a view to mathematical tractability as much as to theoretical rigour.

replacement of 1 by $S(1^+)$ implies that, no matter how favourable the circumstances, it will never be the case that the probability of not owning a car falls to zero. Calibration of equation 5.7 is undertaken by grouping households in the sample into income bands and using $r_j/n_j$ (where $r_j$ is the number of car-owning households in the $j$th income band, containing $n_j$ observations) as an estimate of $P_j(1^+)$, with the mean of the income band giving the value of the independent variable.

This log-logit specification, as it stands, is not strictly a disaggregate model since there is grouping by income, but this is (a) almost unavoidable given the data sources available, and (b) unlikely to have a serious effect on parameter estimation and significance testing. To test for the influence of household characteristics (other than income) and accessibility stratification, separate calibration was undertaken in order to circumvent the problem of having to introduce discrete variables - such as household size - in a continuous form and with a fixed functional specification.

Data limitations prevented the construction of a comprehensive accessibility measure which both reflects ease of movement and range of potential opportunities. Emphasis is placed here upon the mobility aspect, but even so it is clearly difficult to form an


26. It may be possible to avoid this to some extent by using an 'equivalent adult scale' or to base the analysis on individuals. The latter, however, suffers from the defect of having to make strong assumptions concerning the internal decision-making processes within a household.
entirely satisfactory index of transport quality which reflects all the diverse characteristics of different modes, e.g. reliability, cost, speed, comfort, flexibility, etc. A detailed analysis of accessibility to employment opportunities was, however, conducted. While work has also been undertaken on indices reflecting access to other forms of activity (e.g. shopping and schools), the characteristics of journeys to work suggest that they are likely to exert the greatest single influence on car ownership decisions. In particular the decision to buy the first car seems likely to be strongly influenced by commuting needs rather than leisure priorities. If one accepts this, and assuming all households are in spatial equilibrium, then only the relative ease of movement by car vis-à-vis other modes is relevant. Further, it seems important to capture the main costs associated with alternative journey to work modes. Fairhurst's work using G.L.C. zonally aggregated data, for example, is weak because it simply looks at public transport service frequency factors. For this reason it was decided to construct indices of 'generalised cost' of travel to work for the households concerned, generalised costs being a measure reflecting both financial and time costs of travel.

The accessibility measure adopted is essentially an integral accessibility index which reflects the degree of interconnection for a given point with all other points on the same surface. In brief, it may be seen as a scalar point function of the relative accessibility at that point, i.e.

\[ I_i = \sum_{j=1}^{n} a_{ij} \]

where \( I_i \) is the integral accessibility at the \( i^{th} \) point
and \( a_{ij} \) is the relative accessibility of point \( j \) at \( i \).

Relative accessibility reflects the degree to which two points on the
same surface are connected and may be treated, as in this study, as a
measure of travel cost. The unweighted index above has been shown to
be a special case \(^{(28)}\) and it has been suggested that differential
weights be applied reflecting the utilities of different journey
purposes. The simple index of work-trip accessibility is employed in
this study.

5.3 The Data Base and Variables

The data used for estimation was collected as part of the
WYTCONSULT household transportation survey of West Yorkshire conducted
in 1975. \(^{(29)}\) Some 12,322 addresses were sampled but only 7,812 house-
holds provided sufficient information to assist in a household-based
car ownership study. Refusals, moves and non-locations reduced
responses to 9,963 but of these 2,151 gave insufficient or unreliable
information on household income. The survey covers a range of
different geographical areas in West Yorkshire (see Figure 5.1) and
supplementary analysis of travel behaviour offers information about
public transport quality. Such data permit the assessment of the

28. C.D. Foster:- Comment on 'The measurement of accessibility',

29. WYTCONSULT:- Household interview survey report, West Yorkshire
Transportation Studies: Document 511.

204.
assessments of the importance of accessibility influences on vehicle ownership decisions as well as yielding insights into the influence of the more standard socio-economic household characteristics. For the purposes of this paper, only information on car availability, income and composition of household was extracted and combined with an accessibility index calculated for more than 300 county strategic model zones covering the whole of West Yorkshire. Car availability is used as the dependent variable, rather than car ownership to allow for those households with regular use of firms' cars. Clearly, this induces some distortion, as no related adjustment to the recorded
incomes of such households proved possible.

Households were divided into five types characterised by their composition:

H/H Type 1: 0 employed residents and one non-employed resident
H/H Type 2: 0 employed residents and two or more other residents
H/H Type 3: 1 employed resident and zero or one other resident
H/H Type 4: 1 employed resident and two or more other residents
H/H Type 5: 2 or more employed residents

While these classes do not exactly conform to a household life-cycle there is some similarity. Broadly, types 1 and 2 represent, in the main, pensioners; type 3, young households; type 4 standard family households and type 5 mature families. Of course, this is a gross simplification, but there is evidence from activity analysis studies that stage in the family life cycle is a major influence on travel behaviour and, therefore, seems likely to affect car purchasing decisions. (30)

The assessment of accessibility to work involved the construction of generalised time cost functions for public and private transport which express all the cost elements associated with travel in common time units. (31) Drawing upon previous work on travel time evaluation

31. Generalised money costs are a more widely used measure than generalised time costs because of their early acceptance by the Ministry of Transport in the late 1960s. In fact, there is no clear evidence for preferring one measure to another - the real choice between the two measures should depend upon whether the assumption of constant marginal utility of time is (as assumed here) more realistic than the assumption of a constant marginal utility of money.
the following function is employed for public transport accessibility:

$$t_{pti} = t_{ti} + 1.7t_{WLi} + 2.3t_{WTi} + 1.94t_{ci} \quad \text{Eq. 5.8}$$

where $t_{pti}$ is the generalised time cost of a typical journey to work from zone $i$ in minutes

- $t_{ti}$ is the actual time on the bus/train
- $t_{WLi}$ is the walking time to and from the bus/train
- $t_{WTi}$ is the waiting time
- $t_{ci}$ is the fare level

The generalised time cost by private transport ($t_{car_i}$) involved weighting the distance travelled by a factor of 4.23 per kilometre.

A relative accessibility index reflecting the difference between public and private transport generalised costs was constructed but following initial tests, results proved so similar to a simple public transport measure that they are not presented here. To facilitate computation and to permit a clearer presentation of results the accessibility measure was reduced to a zonal classification with four broad bands, representing decreasing levels of accessibility to work, being defined:

- **Acc Band 1**: Up to 54.3 generalised cost minutes by public transport
- **Acc Band 2**: Between 54.3 and 66.6 generalised cost minutes.
- **Acc Band 3**: Between 66.6 and 77.3 generalised cost minutes
- **Acc Band 4**: Over 77.3 generalised cost minutes

Alternative analysis of this data base using simple elementary analysis by medians suggests that this form of accessibility measure is likely to prove superior to the more conventional crude geographical proxies (e.g. distance from the city centre or an urban/suburban/rural...
Further, at this very simple level of analysis there was evidence of a strong relationship between patterns of ownership and quality of local public transport (see Table 5.1 for some basic tabulations).

<table>
<thead>
<tr>
<th>Public Transport Accessibility</th>
<th>Household Incomes (1975 prices)</th>
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<tr>
<td></td>
<td>£1041-£2080</td>
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<tr>
<td>1</td>
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</tr>
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<td>4</td>
<td>0.07</td>
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Table 5.1
The Percentage of Households in West Yorkshire with at least One Car Available

5.4 Calibration of the Single Equation Model

There are a number of alternative methods of estimating parameters of logit models and several techniques were employed. While there are clearly strong a priori statistical arguments favouring certain procedures, in practical terms there may be trade-offs between statistical purity and economy in application which could make a simple calibration procedure an attractive alternative. All the

Single equation estimates are based upon the variables outlined in the previous section and summarised in Table 5.2. The model fitted is that described by equation 5.7.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
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</thead>
<tbody>
<tr>
<td>( C )</td>
<td>Average number of cars or vans available per thousand households</td>
</tr>
<tr>
<td>( P(0) )</td>
<td>Percentage of households with no cars or vans available</td>
</tr>
<tr>
<td>( P(1) )</td>
<td>Percentage of households with one car or van available</td>
</tr>
<tr>
<td>( P(2) )</td>
<td>Percentage of households with two or more cars or vans available</td>
</tr>
<tr>
<td>( Y )</td>
<td>Household income level, measured in £'s sterling</td>
</tr>
<tr>
<td>( E )</td>
<td>Number of employed residents in the household</td>
</tr>
<tr>
<td>( H )</td>
<td>Number of household residents</td>
</tr>
<tr>
<td>( H/H )</td>
<td>Household structure code:</td>
</tr>
<tr>
<td>1 : 0</td>
<td>0 employed residents and 1 non-employed resident</td>
</tr>
<tr>
<td>2 : 1</td>
<td>2+</td>
</tr>
<tr>
<td>3 : 1</td>
<td>0 or 1</td>
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<tr>
<td>4 : 1</td>
<td>2+</td>
</tr>
<tr>
<td>5 : 2+</td>
<td></td>
</tr>
<tr>
<td>( Z )</td>
<td>Zone type code:</td>
</tr>
<tr>
<td>1 : 0</td>
<td>urban/suburban</td>
</tr>
<tr>
<td>2 : 1</td>
<td>dormitory/rural</td>
</tr>
<tr>
<td>3 : 1</td>
<td>other</td>
</tr>
<tr>
<td>( D )</td>
<td>Residential density code: 4 roughly equal groups by increasing density</td>
</tr>
<tr>
<td>( \text{Acc} )</td>
<td>Mean reduction in generalised time cost to households in that residence zone from having &gt; 0.6 cars available per driving licence compared with being dependent on public transport, assuming a typical distribution of journeys to work, coded into four equal groups:</td>
</tr>
<tr>
<td>1 : 0</td>
<td>gain &lt; 18.2 generalised cost minutes</td>
</tr>
<tr>
<td>2 : 1</td>
<td>18.2-20.7</td>
</tr>
<tr>
<td>3 : 1</td>
<td>20.7-27.4</td>
</tr>
<tr>
<td>4 : 1</td>
<td>&gt; 27.4</td>
</tr>
</tbody>
</table>

Table 5.2

Notation Adopted for Variables Used in the West Yorkshire Car Ownership Study

209.
There are three main ways in which log-logit models of this type may be fitted - (i) Maximum Likelihood, (ii) Direct (i.e. Non-Linear) Least Squares and (iii) Minimum Logit $\chi^2$.

(i) Maximum Likelihood is the method favoured by Bates, Gunn and Roberts. (33) Values of $a$, $b$ and $S(1+)$ are chosen for which the probability of the observed $(r_j, n_j)$ values occurring is greatest, given the model form. The main advantages of this method are the relative ease of allowing $S(1+)$ to be estimated, rather than being pre-set, and the availability, as a by-product, of a rough estimate of the variance-covariance matrix, which is provided by the inverse of the matrix of second derivatives - this inverse being required by the iteration procedure which calculates the parameter values. Maximum Likelihood estimates are asymptotically unbiased minimum variance estimates. Minimum Logit $\chi^2$ estimates share this property. (34) Use of Maximum Likelihood methods, however, does require a specialised computer programme and even then obtaining estimates of the parameters is unlikely to be straightforward.

(ii) Non-Linear Least Squares involved finding values of $a$, $b$ and, possibly, $S(1+)$ if this is not pre-set, that minimise $\sum w_j r_j^2$, where the $w_j$ are appropriately chosen weights. In order to avoid the problem of heteroscedasticity each group should be weighted by the inverse of its variance. However, the variances of $P_i(1+)$, or $\frac{r_j}{n_j}$


are estimated by \( \frac{1}{n_j} \left( \frac{r_j}{n_j} \right) \left( \frac{n_j - r_j}{n_j} \right) \), the inverses of which are unsuitable for use as weights, particularly when either \( r_j \) or \( (n_j - r_j) \) is close to zero. Again, a specialised computer programme is necessary for calibration. It is advisable to use the \( n_j \) as weights, so that the method involves minimising \( \sum u_j^2 n_j^2 \).

(iii) Minimum Logit \( \chi^2 \) involves finding values of \( a \) and \( b \) which minimise the sum of squares

\[
\sum \left\{ \log \left( \frac{r_j}{n_j - r_j + \frac{1}{2}} \right) - a - b \log y_j \right\}^2 W_j^2
\]

where \( W_j = \frac{r_j (n_j - r_j)}{n_j} \)

This form assumes \( S(1+) = 1 \), but this may be relaxed by replacing \( \frac{r_j + \frac{1}{2}}{n_j - r_j + \frac{1}{2}} \) by \( \frac{r_j + \frac{1}{2}}{n_j S(1+) - r_j + \frac{1}{2}} \), although this would make the weights even more of an approximation than is ready the case. Consequently, under the 'least squares' column of Table 5.3 the initial set of weights are employed. The "+1" terms are recommended by Anscombe\(^\text{(35)}\) in order to reduce bias in the estimators and, together with the weighting system, overcome the problem of what to do with cases where \( r_j = 0 \) or \( n_j \). Anscombe in fact advised the use of the weights \( W_j \) above where these are individually greater than unity, and zero otherwise, but this would appear to throw away an excessive amount of information. Cox\(^\text{(36)}\) advises use of the alternative


\(^{36}\) D.R. Cox:-- The Analysis of Binary Data (Methuen, London), 1970.
### Table 5.3

Estimates of $a$, $b$, $\gamma(\{\})$ by Various Methods

<table>
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<tr>
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<tr>
<td>4</td>
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</tr>
</tbody>
</table>

Notes:

1. Least squares fits (corresponding to the Minimum Log Likelihood method)
   \[
   a_j = \ln_{10} \left( \frac{r_j + 1}{x_j - x_j + 1} \right) \approx a + \ln_{10} \gamma(\{\}) + u_j
   \]
   with weights
   \[
   w_j = r_j (\ln_{10} y_j - \ln_{10} x_j)
   \]
   and
   \[
   u_j^2 = 1 - \frac{\text{residual sum of squares}}{\text{total sum of squares}}
   \]

2. Maximum likelihood fits
   \[
   a_j = \frac{\ln_{10} \gamma(\{\}) + u_j}{1 + \gamma(\{\})} + u_j
   \]
   with
   \[
   u_j^2 = 1 - \frac{\text{residual sum of squares}}{\text{total sum of squares}}
   \]

(\(u_j^2\) provides a measure of goodness of fit broadly comparable, but not identical, to the coefficient of determination maximised in Least-Squares fitting.)

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<td>0.37</td>
<td>0.37</td>
<td>0.55</td>
<td>0.55</td>
<td>0.55</td>
<td>0.55</td>
<td>0.55</td>
<td>0.55</td>
<td>0.55</td>
</tr>
</tbody>
</table>

Estimates of $a$, $b$, $\gamma(\{\})$ by Various Methods.
weights:
\[
\frac{n_j (r_j + 1) (n_j - r_j + 1)}{(n_j + 1) (n_j + 2)}
\]

but this makes little difference to the estimates.

Table 5.3 gives a set of estimates, based on the West Yorkshire data, calculated using the Minimum Logit \( \chi^2 \) method and a Maximum Likelihood approach. (The former is termed least squares because estimation involved the use of a weighted least-squares procedure.)

The first column uses the mid-points of the 14 income groups categorised in the WYTCONSULT data as the income measure, whereas the remaining three columns use an estimate of the mean income of people in a given income group. This was a rough measure, based on the total sample, and it can be seen by comparing columns 1 and 2 that this adjustment makes little difference when using least squares.

The signs of \( a \) and \( b \) are as expected, the negative sign of \( b \) indicating that as income increases households are less likely not to own a car.

The figures for \( \£Y(i) \) give the income level (in mid-1975 pounds) at which households are predicted to be just as likely to own a car as not (i.e. the equi-probability income level where \( P(1+) = 0.5 \)).

This income level is positively associated with accessibility. In addition, the estimated absolute values of \( a \) and \( b \) are negatively associated with accessibility. The latter relationship implies that those households in the more accessible zones have, other things being equal, a lower income elasticity of demand for car ownership.

Looking at the different household types the position is less clear. Household type 1, mostly pensioners, has a very high equi-
probability income $f_Y(\xi)$, suggesting that it would require massive income increases to induce the bulk of these households to own cars. However, this may merely be due to the limitations of the data, the larger part of which refers to low income groups, although the close agreement of different estimation techniques, and the reasonably high coefficients of multiple determination would seem to contradict this interpretation. Among the other household types, the only striking feature is that type 5 has considerably lower values of $a$ and $b$ than the others, again indicating a lower income elasticity.

Comparing columns 2 and 3 (i.e. Minimum Logit $\chi^2$ and Maximum Likelihood) it is seen that the $f_Y(\xi)$ figures are very similar. The $R^2$ figures are slightly higher for the Maximum Likelihood estimates, but the $R^2$ values given are not directly comparable. Although the ratios of $a$ to $b$ are very similar for the two methods, in all cases the estimated values of $a$ and $b$ are higher in the Maximum Likelihood estimates, indicating higher income elasticity of demand. The Maximum Likelihood estimates were the more difficult to obtain and the results, taken as a whole, suggest that these estimates are less coherent amongst themselves. This difficulty may be attributable to data weakness as the computer programme has worked well with large data sets.

With $S(1+)$ set equal to unity and using the Maximum Likelihood procedure one can also construct cross-tabulations of equi-probability household incomes to gain additional insights. Table 5.4 gives such a cross-tabulation by public transport accessibility and household type. There is clear evidence from the table that the average income
level at which a household is as likely as not to have a car available falls as the quality of public transport - measured in generalised costs of journey to work trips - deteriorates. Similarly, there are marked differences in the equi-probability income level across household types. Small households with no employed members tend to have a higher level of equi-probability income than those with employed members - a feature anticipated given the predominance of single pensioner households in this group. There are clearly some minor 'inconsistencies' within the table, with some household types exhibiting lower equi-probability incomes despite high levels of accessibility. This may be accounted for by the use of small samples in estimating some relationships, or by omitted socio-economic influences or by inadequate allowance for locational influences - locational patterns may, for example, due to land-use planning actions and housing policy, not be in equilibrium.

<table>
<thead>
<tr>
<th>Household Type</th>
<th>Acc Band 1</th>
<th>Acc Band 2</th>
<th>Acc Band 3</th>
<th>Acc Band 4</th>
<th>All Acc Band</th>
</tr>
</thead>
<tbody>
<tr>
<td>A11</td>
<td>2873</td>
<td>2528</td>
<td>2176</td>
<td>2067</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>5064</td>
<td>3110</td>
<td>2779</td>
<td>4759</td>
<td>3868</td>
</tr>
<tr>
<td>2</td>
<td>2178</td>
<td>4458</td>
<td>2017</td>
<td>1820</td>
<td>2241</td>
</tr>
<tr>
<td>3</td>
<td>2779</td>
<td>2607</td>
<td>2086</td>
<td>2055</td>
<td>2382</td>
</tr>
<tr>
<td>4</td>
<td>2814</td>
<td>1929</td>
<td>1827</td>
<td>2000</td>
<td>2049</td>
</tr>
<tr>
<td>5</td>
<td>2715</td>
<td>2401</td>
<td>2180</td>
<td>1794</td>
<td>2239</td>
</tr>
</tbody>
</table>

Table 5.4

Estimates of Equi-probability Household Income (1975 prices) by Accessibility and Household Type

215.
The final column of Table 5.3, together with Table 5.5, give the results with $S(1+)$ estimated as an additional parameter by the Maximum Likelihood method. Here the bracketed $£Y(!)$ figures refer to the predicted income level at which the probability of a household owning at least one car is equal to half the estimated value of $S(1+)$. Allowing $S(1+)$ to vary destabilises the process of estimation considerably. The equi-probable incomes for the accessibility bands still decrease monotonically, but this is not so for the estimates of $a$ and $b$, although the irregularities are not statistically significant. For the total sample the estimated $S(1+)$ is 0.944, with a standard error of 0.02, significantly different from unity. This figure is broadly in agreement with the 0.95 value for $S(1+)$ found by Bates, Gunn and Roberts. (37)

<table>
<thead>
<tr>
<th></th>
<th>$S(1+)$</th>
<th>SE $(S(1+))$</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALL</td>
<td>0.944</td>
<td>0.020</td>
</tr>
<tr>
<td>H/H TYPE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>1.044</td>
<td>0.953</td>
</tr>
<tr>
<td>2</td>
<td>0.909</td>
<td>0.120</td>
</tr>
<tr>
<td>3</td>
<td>1.038</td>
<td>0.040</td>
</tr>
<tr>
<td>4</td>
<td>&gt;1</td>
<td>Failed to converge</td>
</tr>
<tr>
<td>5</td>
<td>1.199</td>
<td>0.134</td>
</tr>
<tr>
<td>ACC BAND</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.904</td>
<td>0.065</td>
</tr>
<tr>
<td>2</td>
<td>0.871</td>
<td>0.045</td>
</tr>
<tr>
<td>3</td>
<td>0.966</td>
<td>0.036</td>
</tr>
<tr>
<td>4</td>
<td>0.984</td>
<td>0.028</td>
</tr>
</tbody>
</table>

Table 5.5

Maximum Likelihood Estimates of $S(1+)$

The results by household type were disappointing, with no values of $S(1^+)$ significantly below unity. It had been expected that small households would have low saturation levels, but such households tend also to have low income and there were, therefore, insufficient richer households for the model to calibrate properly. The results by accessibility band are more satisfactory. It appears that no matter how rich households become, the half of the population with greatest accessibility will contain about 10% of households without a car, whilst the less accessible half will contain about 2½% of households without a car.

In summary, this section has considered the relative merits of the calibration techniques applicable to log-logit car ownership models. Empirical investigations using West Yorkshire data have shown a small but consistent difference between the parameters derived by the two principal methods. The fact that income elasticities are always higher in models calibrated by Maximum Likelihood is clearly a matter of concern. The Maximum Likelihood method has the advantages of theoretical respectability and greater flexibility, which are to some extent offset by the greater ease of fitting Minimum Logit $\chi^2$ models by weighted linear least squares, particularly with small samples.

5.5 Simultaneous Car Ownership/Trip Generation Models

Quite clearly single equation models of this type have severe limitations. In particular they fail to reflect simultaneities in transport decision-making processes and ignore important feedbacks.
from household actions into policies on transport provision (38) (e.g. households owning cars tend to use public transport less and this, in turn, causes public transport services to be reduced). To make some allowance for these effects, a simultaneous equation system was constructed which incorporates car availability, public transport accessibility and non-work trip rates as endogenous variables. The simultaneous treatment of car ownership and trip generation is in accord with the views of both Oi and Shuldiner and Vickerman (39) who have strongly criticised the use of single equation trip generation models which treat car ownership as a predetermined explanatory variable.

Previous attempts to construct models involving car ownership and trip generation have tended to be both recursive and (with the exception of the limited number of studies cited in section 5.1) aggregate in nature. Kain, (40) for example, typifies the approach, while making the underlying assumptions rather more explicit than many others. He calibrates a nine equation model of residential and travel behaviour in Detroit assuming the following decision chain:

38. This point has already been discussed in more detail in Chapter 3. For an earlier, albeit less complicated, attempt at simultaneous modelling of the form developed here and in the context of public transport services and road traffic congestion, see D. Lewis:- Estimating the influence of public policy on road traffic levels in Greater London - a rejoinder, Journal of Transport Economics and Policy, Vol.12, 1978, pp.99-102.


Besides the obvious statistical and forecasting problems associated with a zone based model, this type of approach - which assumes (a) that car ownership and travel decisions are made within the context of an established residential location and (b) that car ownership is unaffected by journey patterns - ignores important simultaneities in decision-making.

Broadly, the system employed here, seen as equations 5.10 to 5.12 below, attempts to reflect some of the complexities of the relationships involved:

\[
L = \alpha_1 + \beta_1 PT + \beta_2 Y + \beta_3 K
\]  
\[\text{Eq. 5.10}\]

\[
PT = \alpha_2 + \beta_4 T + \beta_5 SEG + \beta_6 OAP
\]  
\[\text{Eq. 5.11}\]

\[
T = \alpha_3 + \beta_7 L + \beta_8 K + \beta_9 E + \beta_{10} H
\]  
\[\text{Eq. 5.12}\]

where

- \(L\) is the logit of a household having one or more cars available
- \(Y\) is household income
- \(SEG\) is the household status (i.e. whether it is in social class A and B)
- \(E\) is the number of employed residents
- \(K\) is the number of children (under 16) per household
- \(OAP\) is the number of household residents who are pensioners
- \(H\) is the number of household members
- \(PT\) is the generalised cost of public transport trips to work
- \(T\) is the number of trips per household.
Car ownership is taken as dependent upon the level of household income, the composition of the household and the quality of local public transport services. The structural equation attempts to reflect the tastes of the household in addition to budget constraints and the quality of public transport accessibility enjoyed. Since many trips by children are made in conjunction with adult trips, a family with children would seem to have an incentive to own a car. The generalised cost of public transport is seen to depend upon the nature of the area being served (as reflected by the social status of residents and the importance of pensioners in the population) and the amount of travel undertaken. Trips themselves are taken, in these equations, to be dependent upon the characteristics of households and car availability. This latter conforms to the conventional, widely used specification of household trip generation.\(^{(41)}\)

Estimation was, given doubts about the exact specification, by two-stage rather than three-stage least squares and the results are produced as equations 5.13-5.15 (t ratios in brackets) below.

\[
\begin{align*}
L &= -1.0011 + 0.006PT + 0.0002Y + 0.024K \\
&\quad (3.70) \quad (14.55) \quad (0.47) \quad \text{Eq. 5.13} \\
\end{align*}
\]

\[
\begin{align*}
PT &= 39.0755 + 2.272 T + 11.560 \text{ SEG} - 11.714 \text{ OAP} \\
&\quad (1.63) \quad (1.22) \quad (-1.47) \quad \text{Eq. 5.14} \\
\end{align*}
\]

\[
\begin{align*}
T &= 2.4565 + 2.143L + 1.388K + 1.626E + 0.556H \\
&\quad (3.51) \quad (3.77) \quad (4.76) \quad (1.13) \quad \text{Eq. 5.15} \\
\end{align*}
\]

The majority of the variables take signs which correspond to a priori expectations. In particular, car availability rises as the generalised cost of public transport increases and the availability of...

\(^{(41)}\) See Oi and Shuldiner, op. cit., and Chapter 2.
a car stimulates, ceteris paribus, households to make more trips. Similarly, income exerts a strong positive influence on household car availability. The fact that many cars are wholly or partly subsidised by employers is consistent with this situation if, as seems to be the case, a company car complements high income rather than substitutes for it. The socio-economic variables are not, however, always consistent with expectation. The quality of public transport service (the inverse of the generalised cost of trip making), would seem to be negatively correlated with the social composition of households, which is as anticipated (SEG groups A and B not placing much emphasis on public transport travel), but to be directly related to the incidence of old age pensioners. This latter phenomenon might be seen as reflecting the social service element in local public transport provision. However, the nature of the PT variable, with its emphasis on work trips, suggests this may not be an adequate explanation, although work trip public transport generalised costs do tend to be highly correlated with non-work public transport trip quality. Trips themselves are, as expected, positively related to the size of households, the number of children and the number of employed residents.

The statistical insignificance of some of the endogenous variables in the structural equations (and especially the low explanatory power of T in equation 5.14) suggests the need for some further development of the system. Since there are clearly differences in the factors influencing work trip making and non-work trip making, trips are, in equations 5.16-5.19, divided according to broad trip purpose. Basically, one would expect work trips (WT) to be strongly influenced by the number of employed residents and, since, in West Yorkshire,
much of the variation in household work trip-making is associated with whether lunch is taken at home or place of work, by the availability of a car. Non-work trips (NWT) are likely to be more closely associated with the size of household, the number of school children and the social status of the household. The results of two-stage least squares calibration of a four equation system are seen in equations 5.16-5.19.

\[
\begin{align*}
L &= 1.0170 + 0.006PT + 0.0002Y \\
   &\quad (4.22) \quad (15.30) \\
\text{Eq. 5.16} \\
PT &= 46.3855 + 16.928WT - 15.633NWT + 27.552SEG \\
   &\quad (4.45) \quad (-3.25) \quad (2.05) \\
\text{Eq. 5.17} \\
NWT &= 1.2639 - 0.023PT + 2.302SEG + 0.465K + 0.88711 \\
   &\quad (-2.51) \quad (4.34) \quad (1.55) \quad (3.21) \\
\text{Eq. 5.18} \\
WT &= 0.4762 + 0.483L + 1.144K + 1.494E \\
   &\quad (3.25) \quad (13.90) \quad (16.07) \\
\text{Eq. 5.19}
\end{align*}
\]

The influence of public transport quality, while still positive with respect to car ownership, is now even more significant and income still appears, as one would expect, to be the major explanatory variable in equation 5.16. The public transport quality variable is now rather more satisfactorily explained, especially when it is remembered that it reflects journey to work quality. The negative relationship between service quality (PT being an inverse measure of this) and work trip generation may be seen as a crude reflection of the high generalised time costs associated with operating public transport in congested conditions (i.e. in areas where work journeys are concentrated). It is also likely to be a reflection of the nature of the PT index which credits households of retired workers as having zero journey-to-work costs. Once again, a high incidence of households in non-manual categories (i.e. social groups A and B)
is negatively related to public transport quality as one might expect. Most of the variables in equations 5.17 and 5.18 take signs consistent with a priori expectation and most are significant. The $K$ variable appears highly significant in equation 5.19, exerting a strong positive influence on work trip making. This otherwise seeming perverse situation, is explained by the composite nature of the WT variable which embraces school trips in addition to work trips. Equation 5.19 is, as one would expect, dominated by the influence of the employed residents variable although the availability of a car does exert some positive influence — probably encouraging the driving of children to school and lunching at home. Interestingly, it is public transport quality which seems to influence non-work trip making rather than the availability of a car. Since the number of children in a household is controlled by the model, this cannot be explained in terms of child trips which are, by necessity, frequently non-car based. Attempts to incorporate car availability into the non-work trip-model did not prove successful.

5.6 Conclusions and Policy Implications

In addition to the technical issues considered, the above analysis gives some general indication that public transport quality can affect car ownership decisions. Superficially this would seem to contradict previous studies which have suggested that motorists are, within wide ranges, insensitive to the quality and cost of public transport and that no significant switch would be achieved by reducing public transport fares or by improving the quality of the services offered.\(^\text{42}\)

It is quite clear from our calculations that equal probability income falls as public transport quality falls. Consequently, if public transport is improved in an area so that its general accessibility classification is, say, raised from Band 2 to Band 1, then this should effectively counteract, in car availability terms, a rise in average annual income in the area of £365 (at 1975 prices). (Table 5.3 indicating that £Y(1), when looking at mean incomes, is £2512 for accessibility Band 2 and £2877 for Band 1.) At the extreme, in fact, improving an area's public transport service so that it moves from a Band 4 to a Band 1 grading would have sufficient impact on car availability to counteract a 38.7 per cent rise in real income levels, all other factors remaining constant. Surprisingly, an improvement in quality in an area of initially poor public transport has a relatively small effect. Improving public transport in an area of Band 4 accessibility so that it reaches a Band 3 level changes only marginally the equal probability of car ownership income level (it would only counteract a 4.2 per cent rise in income).

Improving public transport services for households in existing Band 3 areas to the Band 2 level, however, is sufficient to counteract a 16.1 per cent rise in income. This suggests that there may be a threshold level of public transport provision below which the quality is so poor that nothing short of a substantial improvement will have any major effect to prevent rising car ownership, and availability levels.

The difference between this and earlier studies is that the latter concentrated on relatively short term, modal choice responses. (43)

In the short term, quite simply a person tends to use a car, once purchased, rather than review repeatedly the relative advantages of alternative forms of travel. However, the evidence presented above suggests improved public transport may have a longer term dynamic effect in slowing down the increase in the level of household car ownership which, in turn, will act to restrain car traffic on the roads. It should be said that improved public transport is unlikely actually to reduce car ownership but it can influence the rate at which ownership is growing. The effects of public transport quality and other variables is considered in more detail in the following chapter.
6.1 Introduction

In the previous chapters attention has focused on the actual techniques of transport modelling and forecasting, and especially the role which economics can play in improving such models. At times it has proved useful to comment on the various economic and social factors which influence travel behaviour and particularly the level of car ownership. These factors have not, however, been the central theme of the discussion. This chapter is a complement to the earlier ones (especially Chapters 3 - 5) and considers the ways in which different socio-economic variables may affect car ownership. The emphasis will be on the standard variables of Marshallian analysis — namely, income, price, the prices of other goods and consumer tastes — and there will be little further discussion of the purely mechanistic variables such as time trends which form the main component of extrapolative models. The chapter looks at both the economic justifications which have been advanced for incorporating specific variables (together with the alternative detailed specifications which have been favoured) and at the empirical evidence available to support their inclusion. Data is drawn from a variety of sources, both primary and secondary, although the main emphasis is on the influence of socio-economic variables on British car ownership.

1. This chapter draws heavily upon K.J. Button, A.D. Pearman and A.S. Fowkes: - Car Ownership and Modelling (Gower Press, Aldershot), 1981 - especially Chapter 5. The current author was solely responsible for this chapter.
Many factors influence car ownership levels, both at the local and national level. The intention is not to look at all possible influences, but rather to concentrate on the main variables. In addition, the discussion is concerned with the relevance of variables from a policy point of view. While many factors outside the control of transport policy-makers must, of necessity, enter into any realistic representation of car ownership markets, certain variables are of specific interest to policy-makers, since it is through them that car ownership levels and patterns may be regulated. At the national level, the simple extrapolative modelling framework developed by the Transport and Road Research Laboratory, as was seen in Chapter 3, initially supplemented by 'policy sensitive variables' and subsequently challenged by the Regional Highway Traffic Model approach, partly because it could not tell policy-makers how car ownership would respond to their actions. The types of variable incorporated in car ownership models and their detailed specification should be tailored to answer the specific questions set by transport policy-makers. The basic TRRL approach, for example, was initially intended simply to show long-term trends in car numbers assuming a specific road building policy would be pursued. Changes in road building policy and greater emphasis on traffic restraint now require the incorporation of variables which reflect the new situation. Essentially, a different question is being asked.

When considering policy sensitivity it is, therefore, useful to distinguish between two different forms of policy which may influence transport demand - both may prove to be important in the forecasting context. There are broad macro-economic policies affecting income,
public expenditure, fuel prices, etc. which exert strong influences on car ownership and traffic patterns as a whole. These types of policy are captured in most forms of traffic forecasting framework quite simply because they determine the long term aggregate growth path of travel demand. There are, however, also micro-economic policies affecting traffic management, urban public transport provision, access, etc. upon which local transport demand also depends - essentially these determine the local deviation from national patterns. Consequently, while forecasters of national, and possibly regional, travel behaviour require their methodology only to be sensitive to macro policies, those concerned with local predictions are often interested in the sensitivity of their forecasts to local micro-policies. In this latter case, macro-economic policies may be treated in much less detail, since they are outside of the control of local decision-makers, but they must, nevertheless, be considered if appropriate counter-factuals are to be established.

6.2 The Effect of Income

Economic modellers have traditionally argued that income is one of the main determinants (frequently the main determinant) of consumer durable ownership. A car, being a 'normal good', should have a positive income effect associated with it. Most econometric studies, both time-series and cross-sectional, have incorporated an income variable of some kind. The majority of empirical work has placed great emphasis on establishing the income elasticity of demand for car ownership. Table 6.1 presents the results of a wide range of economic studies. It is clear from the table that there is little
<table>
<thead>
<tr>
<th>Study</th>
<th>Period Covered by Study</th>
<th>Data Source</th>
<th>Income Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evans (1969)^a</td>
<td>1948-64</td>
<td>United States</td>
<td>2.7</td>
</tr>
<tr>
<td>Suits (1956)^a</td>
<td>1930-47 &amp; 1945-56</td>
<td>United States</td>
<td>4.2^a</td>
</tr>
<tr>
<td>Genzer (1962)^b</td>
<td>1953</td>
<td>Great Britain</td>
<td>0.69</td>
</tr>
<tr>
<td>Kain (1964)^b</td>
<td>1953</td>
<td>United States</td>
<td>0.13^f</td>
</tr>
<tr>
<td>Bennett (1967)^b</td>
<td>1955</td>
<td>United States</td>
<td>1.6</td>
</tr>
<tr>
<td>Kain (1964)^b</td>
<td>1956</td>
<td>United States</td>
<td>1.53</td>
</tr>
<tr>
<td>O'Herlihy (1957)^a</td>
<td>1948-61</td>
<td>Great Britain</td>
<td>1.23-2.49^f</td>
</tr>
<tr>
<td>Kain &amp; Bresley (1965)^b</td>
<td>1960</td>
<td>Leeds</td>
<td>0.72</td>
</tr>
<tr>
<td>Smith (1975)^b</td>
<td>1968</td>
<td>United States</td>
<td>0.47-1.04^g</td>
</tr>
<tr>
<td>Sleeman (1969)^b</td>
<td>1966</td>
<td>Less-urbanised British regions</td>
<td>1.76</td>
</tr>
<tr>
<td></td>
<td></td>
<td>More-urbanised British regions</td>
<td>2.89</td>
</tr>
<tr>
<td>Buxton &amp; Rhys (1972)^b</td>
<td>1968</td>
<td>English and Welsh regions</td>
<td>1.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>English regions</td>
<td>1.54</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Less-urbanised English &amp; Welsh counties</td>
<td>0.58</td>
</tr>
<tr>
<td></td>
<td></td>
<td>More-urbanised English &amp; Welsh counties</td>
<td>3.06</td>
</tr>
<tr>
<td></td>
<td>1969</td>
<td>English and Welsh regions</td>
<td>1.33</td>
</tr>
<tr>
<td></td>
<td></td>
<td>English regions</td>
<td>2.56</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Less-urbanised English &amp; Welsh counties</td>
<td>0.52</td>
</tr>
<tr>
<td></td>
<td></td>
<td>More-urbanised English &amp; Welsh counties</td>
<td>2.92</td>
</tr>
<tr>
<td>Shepherd (1972)^a</td>
<td>1955-71</td>
<td>Sydney</td>
<td>0.35^e</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Perth</td>
<td>1.03^f</td>
</tr>
<tr>
<td>Pearson &amp; Button (1976)^c</td>
<td>1965-72</td>
<td>English regions</td>
<td>0.3-0.7^h</td>
</tr>
<tr>
<td>McCarthy (1978)^c</td>
<td>1960, 65, 69</td>
<td>Irish counties</td>
<td>1.6</td>
</tr>
<tr>
<td>Golob &amp; Burns (1978)^b</td>
<td>1965</td>
<td>Detroit</td>
<td>0.3</td>
</tr>
</tbody>
</table>

Notes: (a) Short-run elasticities from time-series (b) Long-run elasticities from cross-sections (c) Pooled cross-section and time-series data (d) Relates only to new cars (e) Calculated from simultaneous models with car ownership treated as an endogenous variable (f) Sensitive to the rate of vehicle appreciation assumed (g) Variation between quarters for 1968 (h) Sensitive to the definition of income


Table 6.1

Estimates of Income Elasticities
consensus as to the magnitude of the income elasticity parameter. (2) However, having said this, allowance must be made for the different techniques which were employed in the works, the various periods and areas studied, and also for the additional variables incorporated in the different models. For example, because of collinearity between income and other (omitted) causal variables, cross-sectional estimates are likely to be over-estimates of true income elasticities. Similarly, time-series estimates might well prove to be under-estimates if there are lagged effects, or if some part of income change is (correctly) identified as transitional, and fails to influence car ownership behaviour. Moreover, some of the studies quoted use pooled data sources, and here economic interpretations are difficult. (3) It is also worth noting that, in addition to the estimates given in Table 6.1, several recent studies have failed to find any significant relationship between car ownership and income (e.g. Fishwick (4) and Button (5) in Great Britain and Sanghi (6) in the United States).

2. Rather more limited listings of income elasticities specific to British national car ownership forecasting are to be found in J.J. Bates:- Letter to the editor, Traffic Engineering and Control, Vol.19, 1978, pp.35-6, and J.C. Tanner:- Choice of model structure for car ownership forecasting, Transport and Road Research Laboratory Supplementary Report 523, 1979.


230.
It appears from this brief overview of econometric studies that considerable care must be taken in specifying and interpreting income variables in car ownership models. Indeed, while most of the studies cited in Table 6.1 use either income or disposable income as their independent variable, there may be good grounds for employing suitably modified variables. A number of arguments have been put forward to support this idea.

6.2-1 The Threshold Income Approach

Income may be thought of as affecting vehicle ownership in two distinct ways: (a) people may require a certain minimum or threshold income before they even consider purchasing a car and (b) once this income has been reached, car ownership will only be considered relative to other priorities. A useful if basic model allowing for these two effects was developed by Harrison (7) taking the general form:

\[ P(1+) = 1 - e^{-\frac{(Y-Y_m)}{K}} \]

Eq. 6.1

where \( P(1+) \) is the probability of a household owning a car

\( Y \) is actual income

\( Y_m \) is the threshold level of income below which the probability of car ownership is zero

and \( K \) is the average value of a car.

In this approach, the threshold level of income is allowed to vary with the cost of living, while the probability of car purchase from income above the threshold is influenced by the price of cars relative to other 'luxury' goods.

Clearly, this type of threshold analysis suffers from the inherent limitation that $Y_m$ must be determined exogenously. One method of circumventing this problem is to adopt a threshold multiple regression model of the type developed by Dagenais (8) in which the dependent (car ownership) variable is fixed at zero until "the concerted action of the independent variables [including income] and the error term induce it to overcome its reaction threshold". This implies that a simple linear threshold regression of car ownership on income would be of the general form shown in Figure 6.1. To date, however, models of the threshold regression type have been relatively crude and have offered little improvement over conventional techniques.

Figure 6.1
The threshold income relationship

A pragmatic alternative to threshold regression is to retain the normal multivariate regression analysis but to adjust \( Y \) to reflect expenditure on necessities which have priority demands on income. Fishwick, (9) for example, adopted an income variable, net of tax and deductions, and adjusted to allow for basic expenditures on housing, fuel and food. Unfortunately, the adjusted variable proved statistically insignificant. Pooled data for the standard English regions covering the period 1965 to 1972, however, do produce a significant elasticity for such a variable, i.e.

\[
C_H = 0.468 + 0.0004Y_m - 0.003CP - 0.35UN + 0.41t \quad \text{Eq. 6.2} \\
R^2 = 0.783
\]

\[
C_H = 0.225 + 0.0005Y - 0.003CP - 0.23UN + 0.031t \quad \text{Eq. 6.3} \\
R^2 = 0.825
\]

where \( C_H \) is cars per household in the standard regions of England (with the south-east divided into London and the remainder)

\( UN \) is the percentage of the male population of each region unemployed

\( CP \) is the percentage of each region's population living in conurbations or cities of over 250,000 inhabitants

and \( t \) is a linear time trend (1965 = 1).

All variables are significant at the 5 per cent level. It is clear that the inclusion of the threshold income variable (equation 6.2), in preference to the standard disposable income measure (equation 6.3), worsens the statistical fit (although there are well known difficulties in using standard \( R^2 \) comparisons with pooled models, especially if there is serial correlation between regions). One explanation for

this failure to capture a threshold effect may be inadequacies in
the Family Expenditure Survey data base as a source for extracting
information on necessary expenditures.

In contrast to the British work, Hutchinson, (10) using data
from 2,253 households in Canberra (Australia) found that while
traditional gross income measures proved adequate in his multinomial
logit model, the significance of income increased if a A$3,000 threshold
was employed (the modified income variable being income minus A$3,000
with a zero value if this proved negative). The rationale presented
was identical to that of Fishwick, namely "a conscious attempt to
create a variable reflecting income over which the household has
reasonable discretion in expenditure". (11) The difficulty with this,
and other attempts at adjusting income to reflect necessary expenditures,
is deciding exactly what is a necessity. This is likely to pose a
particular problem with time-series analysis because tastes may
change substantially over time. In addition, the actual purchase of
a car may have associated with it only a relatively small capital
outlay, which, given the existence of an extensive used car market
and the wide range of models and vintages traded, could make the
notion of a threshold income barrier to ownership rather tenuous.
Of course, insurance and other incidental costs can be quite high for
the new driver. More detailed studies of newcomers to car ownership
are required before a firm conclusion can be reached.

10. J.J. Hutchinson: Multi-variable models of car ownership, Traffic
Engineering and Control, Vol.20, 1979, pp.399-403.
11. Ibid., p.400.
6.2-2 Permanent Disposable Income

While many models of car ownership demand have emphasised that potential consumers are restricted in the funds they have available for car purchasing, either because of prior demands by government or because of higher order expenditure needs, Parish (12) has suggested that even the residual disposable income is too simplistic a variable to employ in car ownership forecasting. He draws an analogy with Friedman's (1957) work on aggregate consumption functions. Broadly, he argues that actual consumption and income over a given period, t, are both divisible into permanent and transitory elements, i.e.

\[ Y_t = Y_{Pt} + Y_{Tt} \]

and

\[ CON_t = CON_{Pt} + CON_{Tt} \]

where \( P \) represents permanent

\( T \) transitory

and \( CON \) consumption.

Permanent income, for example, is average or normal income, while transitory income may be thought of in terms of a windfall gain or loss which is not anticipated. It is argued that permanent consumption is likely to be directly related to a consumer's normal receipts or permanent income because a sensible person will, over a period of time, adjust his expenditure patterns to correspond to what he anticipates to be his probable income level, i.e.

\[ CON_{Pt} = P \left( Y_{Pt} \right) \]

Eq. 6.4


235.
In contrast, the actual income over the period will almost certainly be either greater or less than $Y_{Pt}$ because of unexpected windfall gains or losses. The standard permanent income hypothesis argues that transitory consumption is not fully explained by the unexpected shocks to the consumer's income stream. If this is the case, then cross-sectional studies of consumer behaviour based upon a simple actual income measure will yield poor predictive models, with under-estimated income elasticities. More specifically, the cross-section will embrace many low income earners whose actual income is below their permanent income and many high income earners whose actual income is above their permanent income. A series of such studies undertaken through time is also likely to result in unstable parameters. Since at any point in time consumers base their behaviour on their permanent income, cross-sectional studies should logically attempt to incorporate this variable, rather than a simple disposable income variable, in their analysis. This problem is much more less severe with aggregate time-series studies, since permanent and actual income will be equal because transitory income summed over all individuals will be close to zero unless, for example, there are major changes in the distribution of incomes between the personal and corporate sectors, or similar widespread effects on incomes. Perception of permanent income is likely to be influenced by income in previous years, for example:

$$Y_{Pt} = \lambda (Y_t + \gamma Y_{t-1} + \gamma^2 Y_{t-2} + \ldots + \gamma^n Y_{t-n}) \quad \text{Eq. 6.5}$$

and thus:

$$CON_{Pb} = k\lambda (Y_t + \gamma Y_{t-1} + \gamma^2 Y_{t-2} + \ldots + \gamma^n Y_{t-n}) \quad \text{Eq. 6.6}$$

It is assumed that permanent consumption is a constant proportion of
permanent income. Because, by assumption, $0 < \gamma < 1$, the influence of past income decreases with time.

While this theory has an established history in macro-economics, as well as an intuitively appealing simplicity, its application to car ownership has been limited to testing for its significance and attempting to find useful proxies for permanent, as opposed to actual, income. (An exception is Dagenais\(^\text{13}\), who used a weighted average of incomes over a three-year period in his cross-sectional threshold regression work.) Parish\(^\text{14}\) tested for the importance of the permanent income effect by making the standard assumption that any distortions in his car ownership model resulting from using actual income could be treated as an 'errors in variable' problem. He hypothesised that if income was incorrectly specified it would imply that measurement errors in the independent variable would exceed those in car ownership. Using National Traffic Survey data for 1972/3 in a logit framework, he therefore attempted to assess the magnitude of the errors in variables problem by regressing $Y_t$ on $C_t$ rather than vice versa. While the conventional specification would understate the value of the income parameter if the errors in variable problem existed, the respecification would overstate. Thus some notion of sensitivity could be developed. The results obtained were disappointing, however, with poor equation fits. They do suggest, though, that car ownership growth may be more sensitive to income growth than previous studies have found, with over two-thirds of ownership growth being accounted for by increased income as opposed to

\(^{13}\) Dagenais, op. cit.

\(^{14}\) Parish, op. cit. This approach was also used in the empirical work presented in Chapter 4, pp.182-3.
less than one-half in comparable studies. Attempts to replicate this work at the regional level for 1976 and 1978, however, resulted in both poor equation fits and generally negative signs associated with the income variate. (15)

An alternative approach to the idea of permanent income is that some variable - such as household expenditure (16) or the rateable value of property (17) - which is likely to be highly correlated with permanent income - could be used as a surrogate variable, replacing actual income. Certainly there is extensive evidence that rateable value is correlated with car ownership; a simple regression, for example, using 1978 British county data yields:

\[ C = 0.154 - 0.00001D + 0.0006RA + 0.007 WA \]
\[ R^2 = 0.67 \]  

\[ \text{Eq. 6.8} \]

where

- \( C \) is cars per capita
- \( D \) is population density
- \( RA \) is rateable value.

and

- \( WA \) is percentage of employees in agriculture.

All variables are significant at the 5 per cent level.

The difficulty with this approach is that the surrogate variable is far from a perfect proxy for permanent income and other exogenous factors may influence the relationship in the future.

15. See Chapter 4, pp.179-182.


6.2-3 Car Purchasing Income

The notion of car purchasing income has already been encountered in Chapter 3 in the context of econometric modelling at the national level. This is not strictly a method of adapting actual income data to tap the real explanatory force, but rather a mathematically convenient way of combining the influence of two separate economic variables on car ownership, namely, income and car prices. Quite simply it combines the effects of income change with that of car price and motoring cost changes by deflating income rises not as is conventional by a retail price index but rather with a motoring cost index. It is practically useful in forecasting exercises when the underlying model has been calibrated on cross-sectional data with no explicit motoring cost variable included. The difficulty with this form of variable, however, is that the weighting of the 'income' and 'price' effects must be determined externally and then substituted into the forecasting model.\(^{(18)}\) The weighting scheme employed, therefore, acts as a restriction on the implied long term elasticity estimate and its forecasting reliability is, thus, sensitive to the quality of outside information on the relative weights. Basically, the weights are determined by the current priorities of households which are then assumed to remain constant into the future.

Bates, Gunn and Roberts\(^{(19)}\) used historic data to test whether deflation by a retail price index or a car price index offered the

\[\text{References}\]


239.
best fit. Family Expenditure Survey data for 1965/6 and 1969-75 was pooled using as a model:

\[
P(1+) = \frac{S(1+)}{1 + e^{-a_1 \left( \frac{Y_t}{PR_t} \right)^{-b_1} \left( \frac{P_t}{PR_t} \right)^{-c_1}}}
\]

Eq. 6.9

where \( P(1+) \) : proportion of households owning at least one car

\( S(1+) \) : saturation level of ownership for car owning households

\( Y_t \) : income in year \( t \)

\( P_t \) : price of 'motoring' in year \( t \)

\( PR_t \) : retail price index in year \( t \)

When \( P_t \) was defined in terms of either car running costs or total motoring costs then \( c_1 = 0 \) but when an index of car prices was used \( c_1 = -b_1 \). This latter finding would imply that equation 6.9 reduces to the standard RHTM logit model:

\[
P(1+) = \frac{S(1+)}{1 + e^{-a_1 \left( \frac{Y_t}{FC_t} \right)^{-b_1}}}
\]

Eq. 6.10

where \( PC \) : index of car prices.

The general behaviour of the various time series employed is shown in Figure 6.2. Inspection of the figure suggests that the goodness of fit is attributable to the fact that the car purchase price index looks more like a series with a strong downward trend and only slight cyclical variations about it. It implies that any such downward trend would work equally as well. The coefficient attributed to income, \( b_1 \), has been limited by its fitting over the cross-sections. The car price index is only fitted over time, and its trend-like behaviour suits the requirements of the model. The dramatic change
in this trend since about 1973 goes a considerable way to explain why the RHTM forecasts came into disrepute in the late 1970s and why rather more conventional deflators were applied to income and an additional 'trend' variable (adult population in possession of a full driving licence) was introduced. If one is to incorporate both an income and a price effect it seems more sensible to do so with separate variables rather than impose artificial constraints on their relationship with one another.

![Diagram of trends in the costs of car ownership](image)

**Figure 6.2**

*Trends in the costs of car ownership*

---

6.3 Fuel Prices

The 'price' of motoring falls into three broad categories: the fixed costs of purchase and licencing, the time costs of usage and the financial costs of trip making. Since fuel costs form a large proportion of the latter (and even more if perceived rather than genuine resource costs are considered) changes in them may be thought to exercise a strong influence over car ownership rates. Since fuel prices tend to exhibit only minimal geographical variations, within a region or country, it seems unlikely that fuel prices will ever prove to be a significant variable in cross-sectional studies of car ownership. The effects of fuel price changes over time on the total car stock is also debatable. As shown below, there is evidence that large, long-term increases in the real price of fuel will reduce the demand for car use but the impact on total ownership levels is much less clear. Higher fuel prices seem more likely (unless they are of a hitherto unexperienced magnitude) to change the types of vehicle owned than the overall number. Relatively fuel-efficient cars (usually newer vehicles with small engines) will gain in popularity at the expense of less fuel-economic types. Consequently, the major impact of high fuel prices is likely to be on the composition of the vehicle stock and the use made of it.

21. The perceived costs of motoring are considerably lower than the actual costs but petrol is one of the more apparent cost items. One indication of people's level of perception is given by A.J. Harrison and D.A. Quarmby: The value of time in transport planning, European Conference of Ministers of Transport (OECD, Paris), 1969:

"Including fuel, oil, maintenance, tyres and mile dependent depreciation, most private cars show a marginal cost of between 4p. and 7p. a mile. Various empirical methods indicate 'perceived' costs between 2p. and 4p. a mile [in the period 1966-9]."
Unfortunately, aggregate time series studies are not always helpful in revealing the important interacting underlying trends. In particular, there is evidence at the macro-economic level that fuel price rises tend to depress the level of economic activity within the country, leading to a slower growth in national income. Thus a slowing of the rate of increase in car ownership may not be directly attributable to rising fuel prices, but rather to the 'knock-on effect' of the lower income growth which seems to accompany rises in fuel prices: a simple regression between car ownership and fuel prices is, therefore, inappropriate.

An attempt to circumvent this problem has been made by Mogridge who has undertaken a detailed examination of the UK car markets for the decade from 1966. He incorporates in his analysis the interaction between several sub-markets for cars and between the fixed and variable costs of car ownership. An inverse relationship was confirmed between the average car engine size and the price of petrol. More specifically: "In 1973, with the sudden increase in the price of petrol, average new car size fell ... The effect on the car market was a large increase in the depreciation rates of larger cars, smaller cars remaining steady (thus actually appreciating in current terms with the inflation)". In the short term, Mogridge concluded, there might be a slight deviation from long-term trends in aggregate ownership but, in the longer term, adjustments within the structure of the car stock (particularly with respect to car size)

mean that there is unlikely to be a significant change in general trends. A fuel price elasticity of about -0.1 was all that was suggested by the empirical work. (23) The general conclusion from this, and other U.K. work, is that the direct effect of higher fuel prices on the overall level of car ownership has not, on present evidence, proved important, although the indirect effect, associated with a slower growth in national income, is likely to be significant, and probably explains the slower anticipated growth in U.K. car ownership at least in the late 1970s.

This conclusion is supported by the findings of a pooled provincial time-series car ownership model constructed for Canada by Blomqvist and Haessel. (24) The three-equation simultaneous stock-adjustment model used distinguished between demands for small and large new cars and older cars. The general conclusion for the period 1971-5 is that:

"The partial elasticity of demand for new cars with respect to the price of gasoline was found to be relatively small; however the demand for older cars was found to have a substantial elasticity with respect to the price of gas, and this, coupled with the high cross-price elasticity of new car demand with respect to the price of older cars, indicates an important indirect effect on the demand for new cars of changes in the gas price, most of it affecting large new cars". (25)

While the general conclusion is consistent with Mogridge's work, unfortunately the detail is blurred by the sensitivity of the parameters


25. Ibid., p.488.
calculated to the calibration method employed (i.e. ordinary least squares, two-stage least squares and variance components). This statistical problem stems directly from the inherent difficulty of adequately specifying any interactive model of the car market given the paucity of disaggregate data.

It may be thought that, while petrol prices have little impact on ownership decisions, they may be influential in determining the number of trips generated by owning a car. This is equally untrue. Mogridge (26) estimates the short fuel price car use elasticity to be of the order of \(-0.1\), i.e. people try to retain their existing travel patterns in the short term. This general order of magnitude is also confirmed by Bendtsen (27) in a series of international comparisons. He finds the short term petrol price elasticity of demand for car use to be \(-0.08\) in Australia for 1955/76; \(-0.07\) in Britain for 1973/4; \(-0.08\) in Denmark for 1973/4 and \(-0.12\) for 1979/80, and \(-0.05\) in the United States for 1968/75. In the longer term, especially when any fuel price rise ceases to be seen as temporary, the elasticity is likely to rise as people's travel habits adapt to the new 'permanent' state of affairs.

6.4 Household Composition

The socio-economic characteristics of households have long been recognised to be major determinants of travel behaviour and also to

26. Mogridge, op. cit. This general order of magnitude is also found in Australia, see K. Shou and L.W. Johnson: The short-run price elasticity of demand for petrol in Australia, International Journal of Transport Economics, Vol.6, 1979, pp.357-60.

exert strong influences over car ownership levels and patterns. Households can be characterised in a number of different ways: for example, by their size, level of education, age composition, social status, sex distribution, number of employed members, etc. Heggie (28) offers a rather more complete theory than most of why the socio-economic nature of households is so important in car ownership modelling. In particular, he focuses on the car use 'needs' of households at different stages of their life-cycle and then relates this back to ownership. The difficulty is the existence of high collinearity between the socio-economic type of influences discussed and other influential variables (especially the level of household income). A mature family with several members in employment, for instance, may own more than one car but is also likely to enjoy a high level of household income. Some indication of the 'life-cycle effect' on household car ownership patterns is supplied by a study of 159 dwellings in Reading. Downes (29) compares the car ownership levels of the households living in the dwellings for the two Reading travel surveys (of 1962 and 1971). Clearly a number of moves took place between the surveys, 79 dwellings being occupied by different people in 1971 than 1962, but the data base does permit some general conclusions to be drawn using simple cross-tabular analysis. The interesting finding is that "households which increased employment, presumably through housewives and grown children starting work, increased car ownership at the rate of 0.5 cars per employed person. Households which lost employment,

29. J.D. Downes:- Life cycle changes in household structure and travel characteristics, Transport and Road Research Laboratory Report 930.
through retirement and working children leaving home, reduced car ownership at the lower rate of 0.3 cars per employed person". (30)

Once allowance had been made for a trend rise in car ownership over the period (due to people becoming more car oriented, it was then found that cars per household rose by about 0.4 cars per employed person. The major limitation of this analysis, however, is that, in addition to the smallness of the data base, no information was available on household incomes for 1962. Hence, the interactive effects of one of the most important variables in car ownership modelling could not be controlled.

A look at data for West Yorkshire reveals quite clearly that, once allowance has been made for differences in household income, there are still wide variations in car ownership levels between household types. Table 6.2 offers a categorisation of households in West Yorkshire by income and household structure(s) showing the average level of car availability for each. (31) It is apparent that the expected positive relationship between car availability and household income exists. Further, it is clear from examining the breakdown of car ownership by either the number of household residents (H) or the number of employed residents in the household (E) that anticipated variations in the car availability generally do take

30. Ibid., pp.7-8.

31. The table is taken from A.D. Pearman and K.J. Button:- Car ownership forecasting techniques in Great Britain, Transportation Research Record No.775, 1980, pp.11-16, and is based upon data collected as part of the WYTCONSULT study. One should note that the variable looked at is 'availability' rather than ownership in an attempt to capture some of the effects of company finance.
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Table 6.2

Mean Levels of Car Ownership in West Yorkshire
place. However, the combination of E and H produces interesting results. The 'all incomes' column implies that, with H fixed, C increases with E, but this is largely a consequence of increased employment providing households with larger income, since, when H and Y are held constant, C more often than not falls as E increases.

One feature which this type of analysis highlights is the fact that small and poor households tend to exhibit quite different patterns of behaviour from the remainder. It thus cannot simply be assumed that future increases in income for these groups will cause them to behave like more typical households of today. It seems that such households are likely to be in many ways atypical, and that different types of models may be required if reliable car ownership forecasts are required from them.

Because of the difficulties of interaction between the E and H classifications the composite variable H/H (see Table 5.2 for details), which combines elements of both was examined. This variable corresponds

<table>
<thead>
<tr>
<th></th>
<th>Under £676</th>
<th>£676-£935</th>
<th>£936-£1195</th>
<th>£1196-£1455</th>
<th>£1456-£1715</th>
<th>£1716-£2235</th>
<th>Over £2235</th>
<th>All incomes</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>224</td>
<td>250</td>
<td>492</td>
<td>683</td>
<td>608</td>
<td>832</td>
<td>1137</td>
<td>607</td>
</tr>
<tr>
<td>E = 0</td>
<td>222</td>
<td>77</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>217</td>
</tr>
<tr>
<td>1</td>
<td>186</td>
<td>314</td>
<td>511</td>
<td>712</td>
<td>844</td>
<td>967</td>
<td>1143</td>
<td>590</td>
</tr>
<tr>
<td>2</td>
<td>333</td>
<td>143</td>
<td>429</td>
<td>667</td>
<td>508</td>
<td>772</td>
<td>1053</td>
<td>635</td>
</tr>
<tr>
<td>3+</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>455</td>
<td>813</td>
<td>1238</td>
<td>918</td>
</tr>
<tr>
<td>H = 1</td>
<td>77</td>
<td>214</td>
<td>583</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>282</td>
</tr>
<tr>
<td>2</td>
<td>265</td>
<td>275</td>
<td>489</td>
<td>577</td>
<td>619</td>
<td>800</td>
<td>1118</td>
<td>496</td>
</tr>
<tr>
<td>3</td>
<td>308</td>
<td>0</td>
<td>393</td>
<td>783</td>
<td>730</td>
<td>651</td>
<td>1375</td>
<td>680</td>
</tr>
</tbody>
</table>

32. A parallel study of Oxford data conducted by A.S. Fowkes (An investigation of the car ownership content of the 1966 Oxford Household Survey, ITS Technical Note 2, 1978) yields similar results, viz:-
to some crude notion of a household life-cycle theory. There are significantly different levels of car availability associated with the different structures - those with the highest coding having the highest car availability. When income is controlled, however, the body of the table shows that for richer households, increasing household size reduces car availability.

A final method by which households may be delineated is by their social status. Table 6.2 offers a socio-economic (SEG) breakdown of household car ownership cross-classified by income. The SEG variable is a dominant socio-economic group coding by occupation, the code being that of the 'lowest' of any employed resident. Specifically:

SEG group 1 : Full-time professional and managerial
" " 2 : Full-time other non-manual
" " 3 : Full-time skilled manual
" " 4 : Full-time non-skilled manual
" " 5 : Part-time worker.

Households without workers were given a coding of zero.

The effect of social status for given incomes shows SEG1 to have significantly higher car ownership than other SEG codings. It is generally true, also, that SEG2 has higher car ownership than SEG3, and that SEG3 has higher car ownership than SEG4. This pattern is, however, likely to be a reflection of a wide variety of influences, which are being proxied by the SEG variable. (One which particularly varies with SEG is location.)(33)

33. See Appendix 1 for a further consideration of the influence of household social status based upon an alternative data base. Table 5.6 in the previous chapter also gives some indication of the importance of household status once allowance has been made for the quality of local public transport.

250.
6.5 Accessibility

Income acts as a constraint on levels of vehicle ownership while household characteristics capture some of the influence of the catch-all economic variable 'tastes'. Accessibility measures have been incorporated into car ownership modelling for a different reason. These are attempts to reflect more directly the overall welfare advantages that car ownership can confer on households. Some measures of accessibility do this in an absolute sense by attempting to show what additional opportunities become available following car ownership. Other measures are more concerned with the relative advantages of car ownership contrasted with making use of alternative modes of transport. (34)

There is no agreed definition of accessibility in transport modelling; as Gould (35) says: "accessibility ... is a slippery notion ... one of those common terms that everyone uses until faced with the problem of defining and measuring it". There are also the operational problems of deciding whether there are threshold levels of accessibility which affect decision-making and whether one should employ objective or perceived measures of accessibility in transport modelling exercises. Clearly one must tread with care when using the concept.

Empirical accessibility indices tend to vary in the extent to which they allow for the spatial distribution of opportunities, variations in the cost of travel as perceived by the trip-maker, and

the relationship between the potential net benefits of travel and travel cost.

The more commonly used measures are:

- Distance from the General Post Office
- Travel time from the General Post Office
- Population or Residential Density
- Hansen's formula
  \[ \frac{\sum_{j=1}^{n} w_j \exp(-\beta t_{ij})}{\sum_{j=1}^{n} w_j} \]  
  Eq. 6.11
- Ingram's formula
  \[ \frac{100 \sum_{j=1}^{n} \exp(-t_{ij}^2 \cdot \nu^{-1})}{n} \]  
  Eq. 6.12
- Savigear's formula
  \[ \frac{\sum_{j=1}^{n} w_j}{\sum_{j=1}^{n} w_j \cdot t_{ij}} \]  
  Eq. 6.13
- Modified Ingram's formula
  \[ \frac{\sum_{j=1}^{n} w_j \exp(-t_{ij}^2 \cdot \nu^{-1})}{\sum_{j=1}^{n} w_j} \]  
  Eq. 6.14

where \( t_{ij} \) = travel time from \( i \) to \( j \)  
\( w_j \) = a measure of attractiveness of \( j \)  
\( \beta, \nu \) = coefficients.

Ingram\(^{(36)}\) offers a useful conceptual distinction between relative accessibility, which reflects the degree to which two points on the same surface are connected, and integral accessibility, which reflects the degree of interconnection for a given point with all other points on the same surface. In brief, integral accessibility is a scalar point function of the relative accessibilities at that point, i.e.

\[ ACC_i = \sum_{j=1}^{n} a_{ij} \]  
Eq. 6.15

where \( ACC_i \) is the integral accessibility at the \( i^{th} \) point.

While the notion of relative accessibility can be considered as a measure of travel cost, and thus fitted into conventional utility theory, the concept of integral accessibility poses problems of weighting the utilities of different journey purposes — the unweighted measure seen in equation 6.15 being a special case.

The relevance of accessibility in applied car ownership work is generally couched in terms of the need for private transport for trip making (especially with regard to the journey to work) and the quality of public transport services. There is also often mention of the actual need for trip making per se to permit a full range of social and employment opportunities to be enjoyed. Measures of accessibility may either be in the form of surrogate variables or as indices which attempt to measure more directly the level of access enjoyed by a household.

The most common surrogate is the population or residential density of an area (or, at the regional level, the percentage of the population living in conurbations has been used for a similar purposes; see equations 6.5 and 6.6). Spatial variables of this type are thought to act as proxies for three important influences on car ownership:

1. The close proximity to shops, schools, centres of recreation and places of employment generally associated with urban or other densely populated areas reduces the number of regular journeys a person need make and, in consequence, makes car ownership less attractive.

2. Densely populated areas generally result in high levels of traffic congestion forcing up the generalised costs of car
use vis-à-vis rural driving. Attempts to reduce congestion by traffic management and other means put restraints on driver freedom, even if traffic speeds are increased, i.e. network and control congestion results.

(3) High population density increases the potential economic efficiency of public transport modes with a consequential increase in service quality and possibly lower fares.

The general effect of these spatial and other factors has long been recognised (in addition to population density, Tanner, (37) found 'distance North' to have a significant influence on car ownership, while Fishwick (38) employed a 'distance from London' variable) and has been clearly illustrated by reference to the West Yorkshire data in Chapter 4. The problem with using such information in a forecasting context, however, is that the underlying causes of these differences may vary over time. Consequently, a more direct, and precise accessibility measure should be sought. Fairhurst (39) attempted to do this explicitly in terms of public transport quality by developing an index for both bus and rail public transport in London (see Chapter 3). The variable, used in a logit framework, proved both to be significant and to have the anticipated negative effect on vehicle ownership. The limitations of his particular specification of public transport accessibility lie in both the limited characteristics of service quality considered


(i.e. service frequency) and the implicit assumption that non-work travel influenced car ownership (mid-day characteristics were used). It is also essentially an integral accessibility measure with all the associated problems of economic interpretation.

The use of a more sophisticated public transport accessibility index based upon the generalised time costs of journeys to work has already been mentioned in connection with disaggregate car ownership modelling in Chapter 5. Such an index seems likely to pick up the actual costs of public transport trip making more fully than the Fairhurst concept, and also is directly related to work journeys. The index, in addition, is more akin to a measure of relative accessibility reflecting generalised travel costs for the established work trips made by each household.

American data, taken from the San Francisco Bay Area in 1975, also gives general support to the importance of accessibility in influencing car ownership.40 Using a multinomial logit framework, this work indicates that an accessibility index (constructed as a measure of the ease of travel to non-work destinations) plays a consistent role in influencing whether a household will own a car and, if ownership is adopted, the number of vehicles covered. Train41 concludes: "as expected, an increase in the ease of travel to non-work destinations by transit increases the probability of owning no autos ... The estimated coefficients of 'accessibility to

41. Ibid., p.365-6.
non-work destinations by auto or transit indicate that as the ease of travel by auto increases (and the ease of travel by transit remains constant) the probability of owning one auto over none increases, the probability of owning two autos over one or none increases, and the probability of owning three or more autos over two or less increases."

While the West Yorkshire and San Francisco results both support the hypothesis that accessibility plays a part in influencing household car ownership levels, it is interesting that the former concentrates on access to work places while the latter defines accessibility in terms of non-work trip making. This is to some extent illusory, however, since the American work also incorporates an 'aggregate work-trip utility' variable which represents in the model the simultaneity of mode choice for journeys to work with car ownership decisions. This tends to make the model more complete, taking account of both travel to work and travel to non-work destinations in car ownership decision-making. The data requirements for such a model could not be met in West Yorkshire.

6.6 Summary and Conclusions

The variables affecting car ownership decisions are numerous. This chapter has attempted to assess the impact of the main socio-economic variables. It is clear that while conventional variables such as income are likely to exert a major influence over car ownership levels, the exact specification of the relationship is a complex one. The influence suggested by econometric analysis is complicated by the type of data base employed, the time period under review and
the additional variables in the model. The problem is compounded with the growth in company car provision (or at least finance to reduce the monetary burden of car ownership) and the difficulty of deciding what exactly constitutes 'disposable income' in the context of acquiring such a major consumer durable. The evidence offered in the chapter suggests that in the forecasting role, somewhat simpler definitions of income may yield adequate forecasting parameters than are often employed.

The evidence of this, and the preceding chapter, also suggests that there are severe problems of multicollinearity between many of the conventional variables employed in car ownership modelling. In particular, it suggests that there exist quite important interactive effects between several of the standard variables employed in car ownership forecasting work at the local level. While this may not, of course, be held to be a problem by a forecaster of the inter-relationship between the 'independent' variables thought to be invariant with time, it does throw up difficulties if temporal change is anticipated or if one wishes to employ the model in a different location. Certainly, there seems to be a strong indication, for example, that tastes are correlated with household structure but that this relationship is far from a constant one. The use of statistical techniques at the modelling stage (e.g. factor analysis) to examine the degree of collinearity and to isolate the main explanatory variables may partially solve the static, calibration problem but dynamic procedures may be required to reduce forecasting...
difficulties.\textsuperscript{(42)}

One variable which has emerged as being of particular significance is the accessibility variable. The detailed definition of accessibility has proved difficult but, nevertheless, even the crudest proxies prove to be significant at the local level. With the changing emphasis of transport policy, and the increased importance of traffic management, it is likely that more exact and sensitive specifications of this variable will be required in future transport forecasting. Once again, it is apparent from the work in this and the previous chapter that some form of simultaneous relationship exists between the quality of accessibility, trip making and car ownership and that it is important when modelling to take due cognisance of this.

Finally, the family or household life-cycle seems to have an important bearing on car ownership levels. Crude proxies of the type reviewed in this chapter (e.g. SEG, number of employed residents, household size, etc.) only tend to pick up part of this very important variable. Although it may be possible to glean some information on the exact nature of the influence involved by detailed and careful (probably non-statistical) study of cross-sectional data the most promising line of research would seem to be via a panel survey.\textsuperscript{(43)}

\textsuperscript{42} Dynamic models of this type are rare but a crude attempt to construct such a model is to be found in K.J. Button and A.D. Pearman:- The theory and practice of car ownership forecasting, in E.J. Visser (ed.), Transport Decisions in an Age of Uncertainty (Martinus Nijhoff, the Hague), 1977, pp.137-44. It is clear from even this very basic model that application of dynamic analysis would, in practice, be far from straightforward.

\textsuperscript{43} An attempt at such a panel survey has just begun in Australia, see D.A. Hensher and T. Maneefield:- A structured logit model of automobile acquisition and type choice: some preliminary evidence, Mimeo, Macquarie University, 1981.
This would involve continuously (annually) reviewing the same, stratified panel of households over an extensive period to find how their decisions change with the family cycle. Quite clearly this is beyond the scope of this particular piece of work.
7.1 Introduction

This chapter serves two main functions. Firstly, it offers a slightly more practical assessment of the various approaches to transport demand forecasting, again concentrating mainly on the car ownership dimension. While the preceding chapters have been concerned with technical matters and a consideration of the role played by various socio-economic variables in influencing car ownership levels, little has been said about the rather more pragmatic issue of which modelling framework is best suited to meet the needs of transport planners. The following section therefore offers a much more practical critique of modelling techniques. Secondly, although this is a thesis it does seem appropriate to violate certain of the older conventions and to offer some speculations and suggestions about how transport demand modelling should evolve in the future. To date much of the development in transport modelling and forecasting since the 1960s has been concerned with adopting and refining an established methodology to meet the changing demands of decision-makers, but now there may be the need for a radically different approach.

1. Much of the material contained within this chapter is drawn from K.J. Button: The practical problems of traffic forecasting, in K.J. Button and A.D. Pearman (eds), The Practice of Transport Investment Appraisal (Gower Press, Aldershot), 1982.
7.2 The Practical Criteria

We have already seen that there is no such thing as a 'perfect' forecast in transport, the levels of uncertainty are too great, the potential possibilities too large and 'ideal' procedures too costly. As one commentator said, following the presentation of a paper by J.C. Tanner (2) on traffic forecasting to the Royal Statistical Society, "For he who would forecast traffic up to 30 years ahead has an impossible task. On the one hand, the numbers of vehicles and their journeys are outcomes of demographic, social, political and economic factors, of international trade and travel, and none of these permit reliable forecasts. On the other hand, the available data are poor in predicture information and hard to get; simple statistical models are impossible to formulate validly; and consequently reliable statistical methods hardly exist. Any choice of approach and method must be a flagrant compromise, and identifiable weaknesses are inevitable." Despite these problems forecasts must be made and are made, the issue focuses on the best practical compromise possible.

Any traffic forecasting, as we have seen, involves a series of stages. Firstly, one has to decide exactly what it is that is to be predicted, then there is the need to collect information on the existing situation prior to constructing some form of forecasting model. From this model one produces projections by feeding in further information about future trends in exogenous variables. In many cases, therefore, it may prove more important to meet certain

criteria in relation to that particular stage rather than obtain the most accurate result possible. For example, financial budgets may necessitate sub-optimally small samples being used or lack of computing capacity require the use of rather simple modelling techniques. Consequently the quality one is looking for in a forecasting methodology is not exclusively accuracy although this will, obviously, be of considerable importance. Other important qualities may include, for example, economy, flexibility, policy sensitivity, speed, theoretical respectability, etc. In many cases the choice of forecasting method is determined by a process more akin to satisficing than maximising, the approach which is preferred is accepted because it meets certain minimum, satisfactory levels for each of the various criteria.

One of the major problems in traffic forecasting is that the qualities sought by the forecaster may not coincide with those preferred by those responsible for the actual appraisal. National car ownership forecasts employed in trunk road appraisal have since the mid-1970s, for example, been given within a maximum and minimum band while those responsible for road construction tend to base their decisions on a single expected future level of car ownership (and, ipso facto, traffic flow) at some target date. Clearly this raises problems at the interface between forecasting and appraisal which has resulted in some modifications to the latter. Such problems will be discussed in more detail below.

The most frequently sought qualities in a traffic forecasting framework may be considered under the following general headings:

7.2-1 Accuracy

Accuracy is not quite the simple concept it is often thought to be. There is clearly the obvious distinction between short-term and long-term accuracy whereby a forecasting methodology may yield extremely good predictions of traffic volumes over a period of two or three years but thereafter cease to yield useful results. Alternatively long-term forecasting models may be extremely unreliable in the short term. If we look at Figure 7.1, for example, which traces out the growth in car ownership per capita in Great Britain between 1942 and 1975, it is clear that while a straight-line extrapolation from 1942-1951 onwards would produce reasonable forecasts for several years, by the end of the period serious under-predictions would result. Possibly of more importance, but an area subject to considerable neglect, are the short-term inaccuracies which often accompany long-term forecasts. In many cases, provided the long-term projections are reasonable, short-term fluctuations around the projected trend are of little consequence and, in some instances, the important point is often the rather simple one of whether car ownership is going to grow at all irrespective of some detailed rate.

The use of extrapolative forecasts of car ownership in inter-urban road investment appraisals illustrates the importance of long and short-term considerations. The benefits of road investment accumulate as a consequence of use of a road, which is assessed over a
Figure 7.1
Per capita car ownership in Great Britain 1942-1975

forecast period, typically twenty-five years. Because of the
discounting procedure within cost-benefit analysis, inaccuracies
towards the end of the forecast period are of relatively little
importance, so that slightly incorrect car ownership projections will
not greatly affect assessed benefits. The same is not so clearly
true with regard to costs, as road designs are based in the first
instance on expected traffic levels fifteen years after the opening
of the new road, say again, twenty-five years ahead. If traffic
forecasts are so grossly inaccurate as to cause a quite inappropriate
scale of provision (say a three-lane motorway instead of a two-lane
one), then this will have a major effect, as most costs are incurred
at the start of a project's life and are not greatly diminished by
discounting. For forecasting at local level of aggregation such
arguments hold less weight because the types of policy under assessment frequently have much shorter term consequences and are such that it is reasonable to expect that levels of car ownership and use will be significantly affected by them. Consequently, accuracy must be defined in the context of the use to which forecasts are put rather than in terms of pure predictive power per se.

Accuracy has a second dimension involving the confidence with which the predictions may be taken. Normally, and almost by convention, single figure projections are given of, for example, the expected number of cars or volume of traffic over a specific route for a specified target date with some indication of the path followed over the intervening period. Such forecasts clearly involve making a number of assumptions concerning the expected values of various influence variables. Each of these will, however, in fact have associated with them a distribution of possible outcomes. Thus, if these distributions are known it is possible to subject these forecasts to various sensitivity tests and to obtain a range for the probable outcome. The users of forecasts, however, are often not altogether indifferent as to which of the two sides of the distribution around the expected value actual traffic flows fall. In the case of a road appraisal, for example, if the actual outcome falls within the lower range of the traffic forecast then reliance on a more central prediction could result in excess capacity being provided and resources wasted. Alternatively, if the outcome is higher than the designer had assumed there are likely to be heavy congestion costs and incremental adjustments to expand capacity are likely to be expensive.
On balance, the Department of Transport (4) seems to feel the latter situation the most undesirable, i.e. "The penalty of providing inadequate capacity at junctions, or of building a carriageway with inadequate strength to withstand the demand on it from heavy vehicle traffic can be higher in relation to initial cost, than the penalties of under developing roads in other respects. The cost of remedying such faults when the road is in use and near its capacity can be very considerable." Consequently, one of the main forms of accuracy which is often sought relates to the distribution of probable outcomes rather than the actual expected single figure projection.

Finally, there are certain, totally unpredictable, factors which can completely destroy the basis upon which forecasts are based and thus render them totally inaccurate. (It is worth noting, however, that even when crises do not distort the picture, a considerable proportion of the inaccuracy in most traffic forecasts has proved to be a consequence of inaccurate projections of the independent variables, rather than calibration errors or flaws in the model structure per se.) The oil crisis of 1974, for instance, is the classic example of an unpredictable event; here an unforeseen rise in fuel prices caused a sudden and dramatic change in the demand for travel. Almost by definition it is impossible to allow for such events when forecasting but the problem may be recognised if forecasting is conducted on two levels. Pearman and Button (5) suggest


that at the lower level forecasting should follow one of the currently established type of model, although offering more information about the robustness of projections in the light of short-lived distortions to 'normal' patterns of behaviour. (Using, for instance, simulation techniques of the Monte Carlo kind.) The second, higher level projections would involve 'scenario' analysis and would provide planners and decision-makers with some, not necessarily quantified, guide to the possible impact of sudden, dramatic changes in the environment in which transport operates. This is clearly a move away from the mechanistic approach of offering 'exact' forecasts and, by necessity, use of the predictions would involve a greater degree of subjective application but the final outcome may prove to be more accurate forecasts in the wider sense.

7.2-2 Theoretical Consistency

The 29 June 1974 issue of *Business Week* expressed the view that "a forecast, essentially, is the statement of a theory with specific values instead of abstractions. When the forecast goes seriously wrong, it suggests that something is wrong with the theory". Quite obviously one can question the validity of this statement - forecasts may go wrong, for example, because of inappropriate application of a perfectly sound theory or because of defective calibration of essential parameters without, in either case, the underlying theory being defective. Nevertheless, the theoretical foundation of a forecasting model is important. What are the desirable properties sought in a forecasting model? Certainly replication of the real world is both impossible and, given the problems of forecasting forward exogenous
variables, even undesirable. John Maynard Keynes argued over forty years ago that "The objective of a model is to segregate the semi-permanent or relatively constant factors from those which are transitory or fluctuating so as to develop a logical way of thinking about the latter, and of understanding the time sequences to which they give rise in particular cases". The difficulty then becomes one of deciding, in the forecasting context, what are semi-permanent factors? A semi-tautological answer is supplied by Friedman (6) who argues that "Complete 'realism' is clearly unattainable, and the question whether a theory is realistic 'enough' can be settled only by seeing whether it yields predictions that are good enough for the purpose in hand or that are better than predictions from alternative theories". An alternative and opposite view is expressed by Ben-Akiva (7) when supporting the idea of disaggregate causal models, namely "In general, it is impossible to determine the correct specification of a model from data analysis. It should be determined from theory or a priori knowledge based upon experience with, and understanding of, the phenomenon to be modelled".

One's view of the importance and the desirability of a firm theoretical foundation to underlie traffic forecasts, however, often depends upon what it is that one wishes to obtain from the forecasting exercise. If it is simply numerically accurate forecasts then the theoretical base may prove less important. The design and calibration of elegant and theoretically sound mathematical models of car ownership

in this case is transcended by the practical necessity to produce accurate numerical forecasts for policy purposes. Alternatively, if one accepts Heggie's\(^8\) view that traffic models should, in addition to providing predictions, assist in understanding and explaining behaviour and aid in policy formulation, then theoretical considerations increase in importance. Further, if the forecasts are to be treated as neutral, irreversible facts then once again the underlying importance of theory is likely to be overshadowed by the need for accuracy. Should the forecasts, however, be seen as sensitive to the actions of policy-makers, either those directly involved in the transport sector or those concerned with broader macro-economic policy, then an understanding of the workings of the transport market together with a sound theoretical appreciation of the ways in which policy affects this market becomes important.

There is the further difficulty with Friedman's view, hinted at by Ben-Akiva, that when actually projecting car ownership or traffic flows forward it is, of course, impossible to know how accurate the forecasts are going to be. The normal criteria, therefore, employed in transport forecasting (especially at the local level) is to accept a model which offers a good (usually the best) statistical 'explanation' of the current pattern of behaviour. The difficulty is that it is often very easy to get models which fit cross-sectional data or past time series but, because of the lack or weakness of any firm theoretical foundation are, in fact, extremely poor predictors. This is fairly easily demonstrated empirically by taking a simple regional car

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ownership model.

Many studies of car ownership rely for their explanatory powers upon variables which have no readily identifiable economic rationale. In some cases attempts have been made to justify the use of such variables by adopting the argument that they are acting as proxies or surrogates for influences which are either not immediately quantifiable or for which there is no readily available data. These 'artificial' variables are of three types. Firstly, there are actual variables which may add considerably to the explanatory power of a regression model but which have only an indirect claim to being called explanatory variables. Spatial parameters such as residential density or the percentage of a region's population living in conurbations fall into this category. Ex post justifications for their inclusion, as we have seen, usually mention their role as proxy for local public transport quality or for accessibility more generally defined. An example of their importance can be seen in the following equation (representing a fairly standard multivariate regression approach) based upon pooled data from English and Welsh standard regions for 1965-72:

\[ C = -0.762 + 0.0008Y - 0.018PD + 0.027U + 2.182B + 3.317S + 0.008H \]

\[ R^2 = 0.7226 \]

where

- \( C \) = Cars per household
- \( Y \) = Household income net of direct taxes and other deductions
- \( PD \) = Population density
- \( U \) = Level of unemployment (%)
Employment in basic industries (% of total labour force)

Social Economic Group (% in SEGs 1, 2, 3, 4 and 13)

Household size

* indicate the variables significant at the 99% level.

One may reject the model in detail because of certain ambiguities in some of the coefficients (e.g., car ownership appears to rise with the level of unemployment) but in practice the PD variable is likely to be retained by forecasters because of its high level of significance and because it would be argued that one would expect car ownership to be lower in regions which are densely populated and likely to have adequate public transport. For forecasting, this is not very helpful, however, because the planner is likely to alter the relationship between density and public transport as part of the planning exercise.

A further 'artificial' variable is a time trend. This, it is argued, indicates the autonomous growth in car ownership which cannot easily be explained in terms of economic influences. We can introduce this into the above model very easily:

\[
C = -1.7367 + 0.0003Y^* - 0.066PD - 0.012U + 2.112B^* + 2.790S^* + 0.500H^* + 0.038T^* \quad \text{Eq. 7.2}
\]

\[
R^2 = 0.8605
\]

where \(T = \) A time trend with 1965 = 1.

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9. It may be argued that 'time' reflects changes in tastes or, following J. Burrell (Recent developments in car ownership forecasting, in PTRC, Urban Traffic Model Research, PTRC-SAM, 1972) may indicate the increased car-orientation of society. If so, then, to use this notion in forecasting must assume tastes will continue to change in a predictable way (i.e. correlated with time) in the future.
The introduction of T improves the 'explanatory power' of the model in terms of equation fit ($R^2$) and also results in some of the traditional economic variables, notably unemployment, reverting to a coefficient exhibiting the sign one would anticipate. The limitation for forecasting of this approach is that the time trend must be assumed to continue unchanged in the future. In many ways this is an identical assumption to that underlying the extrapolation techniques discussed above and is open to similar criticisms.

Finally, artificial variables can be in the form of 'dummies' which take the value 1 if the region falls into some specified category and a zero otherwise. If we look at Figures 7.2(a) and (b) showing the growth paths of regional car ownership over the period in question we see that three groupings emerge: (a) North-West, Yorkshire and Humberside and North, (b) Greater London, East Midlands and West Midlands and (c) South-East, South-West and East Anglia. For statistical reasons we only use dummy variables for the last two groups. The following regression is obtained:

$$C = 0.567 + 0.0003Y^* - 0.011PD^* + 0.025U^* - 0.250B + 0.161S - 0.167H + 0.259D^*_1 + 0.155D^*_2$$

Eq. 7.3

$$R^2 = 0.8957$$

where $D_1 = 1$ if the observation is in regional group (c)
   0 otherwise

$D_2 = 1$ if the observation is in regional group (b)
   0 otherwise

10. Table 4.1 in Chapter 4 gives a rather longer term view of the situation. See also, K.J. Button and A.D. Pearman:- The theory and practice of car ownership forecasting, in E.J. Visser (ed.), Transport Decisions in an Age of Uncertainty (Martinus Nijhoff, the Hague), 1977, pp.137-144.
In purely mechanical terms this equation form is a considerable advance on those preceding it; the $R^2$ value is higher, there is less multicollinearity, autocorrelation is considerably reduced\(^{(11)}\) and the constant term has a more reasonable positive value. For forecasting purposes, however, one must assume that the parallel growth trends of the three regional groupings will continue with neither any convergence nor divergence and that individual regions will continue to exhibit the

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11. Figure 4.4 gives some impression of the effect of introducing regional dummy variables on the error term, albeit for a slightly different specification.
same trends as their parent group. Such assumptions are unlikely to be valid in the longer term but without any theoretical knowledge of why the initial groups occur it is impossible to base forecasts on any other footing.

7.2-3 Flexibility

Flexibility in forecasting may take a variety of forms. Firstly, it is often useful if a forecasting framework may be used in a variety of applications. Throughout the 1960s the majority of U.K. transport policy initiatives focused on the large-scale expansion of transport infrastructure both at the urban and inter-urban level\(^{(12)}\) (the motorways system, for example, expanded from 153 kilometers in 1960 to 2,483 kilometers in 1979, while nearly 2,000 kilometers of trunk roads were made into dual carriageways between 1970 and 1979) but subsequently the emphasis has moved away from comprehensive, investment intensive transport planning and been replaced by a rather more ad hoc, piecemeal approach.\(^{(13)}\) Consequently, traffic forecasting models need to be adaptable, capable of meeting the needs of those involved in relatively small-scale road improvements, parking schemes, public transport subsidies, car-pooling arrangements, pollution controls, vehicle restriction policies, etc.


A forecasting model may also need to be flexible to permit the testing of different policy options, i.e. it is often desirable that it is 'policy sensitive'. This feature of demand forecasting models tended to be less important where an overriding philosophy (e.g. the idea in the 1950s that all demands for road space should be met) dominated official transport policy but has become rather more desirable in recent years with the acceptance that transport policy should seek to satisfy a diverse range of socio-economic goals rather than simply fulfill stipulated traffic targets. Policy began, from the mid-1970s, to emphasize a need to reverse previous trends, using incentives to persuade the public to break existing habits, especially those relating to urban car use. In the United Kingdom such new policies were pursued in several provincial town centres with some vigour. A 'Balanced Transport' policy was, for instance, introduced into Oxford by adopting a package including escalating parking charges, extraction of on-street parking, closure of some streets and attempts in general aimed at making public transport more attractive. The 'zone and collar scheme' tried in Nottingham was a further example. This overall change in the basis of transport planning can perhaps be traced back to the late 1960s when the transport element of the Greater London Development Plan came under considerable criticism for its excessive reliance on the then conventional road building philosophy, i.e. "... there is ample evidence to support our view that, whether for reasons of administrative difficulty, political reluctance, or inertia, the potentials of management measures, and of restraint by parking controls, have not been adequately used and are far from
sufficiently exploited". (14)

A methodology may be flexible in a number of different ways. It can, as mentioned above, be flexible in the areas of application but it may also be flexible in terms of the level of aggregation at which it may be applied. The logistic curve fitting technique of car ownership forecasting was widely used at different levels of aggregation in the early 1970s, for example, but subsequently it proved inadequate, especially at the local, urban level. Subsequently, the 'disaggregate' causal approach has been applied at several levels of aggregation (e.g. from the RHTM national forecasts to local studies of car pooling) (15) but again this has not proved itself quite as flexible as initial advocates hoped. In this sense, flexibility seems to have alluded car ownership forecasters.

7.2-4 Economy

Traffic forecasting may be expensive and one oft sought quality in a forecasting framework is economy. Economy may result from several features. Data collection is normally a labour intensive exercise and consequently costly. Use of census and other easily accessible official statistics offers economies and was one of the

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reasons for the development of category analysis forecasting procedures. (16) Where sample surveys are employed, the forecaster may seek a methodology which either requires a small data base or one which does not necessitate expensive sampling techniques. The advocates of disaggregate household-based forecasting models, requiring only some 600 or so household surveys, point to the advantages of the method over the 10,000 samples required in the zonally aggregate, sequential model employed in the 1960s. (There has been some question of this apparent advantage in recent work - e.g. by Bates (17) - on the grounds that economy in the data base is only obtained by increasing the potential error in the forecasts.) Activity analysis, which is considered in detail below, also claims economy in sample size - much of the work conducted in Oxford in 1976 using this technique only required a sample of 60 households. The problem is that the surveys themselves are intensive, indepth affairs, involving a carefully selected sample and this, quite clearly, pushes up costs.

Economy may also be achieved in the costs of model calibration and prediction. Calibration is less of a problem today than, say, a decade ago. The development of standard computer software combined with the widespread availability of high-powered computing facilities releases one of the formerly binding constraints which confronted traffic forecasters. Nevertheless in some circumstances, especially

in Third World countries, a simple methodology requiring relatively simple computational aids and technical skills may be a very important quality sought by forecasters.

While the widespread availability of computing facilities does now facilitate the easier and cheaper application of advanced models this availability is also not without its own dangers. In a paper by Pearman and Button,(18) commenting upon some earlier work by Lesley(19) concerned with examining the structure of urban public transport, one such danger became apparent. Lesley had made use of a standard statistical regression software package to appraise the importance of a number of 'macro-parameters' on the public transport system of 34 European cities. His conclusions, however, were based upon regression planes constrained through the origin which, in effect, invalidated the results he obtained given the nature of the statistical 'package' he employed. As the authors said on that occasion, "Regression analysis is deceptively simple and in practical terms even more so since the widespread availability of computer software. This leads to a double danger: misinterpretation of the package itself and the general misuse of regression techniques."(20) Economy in terms of time and cost savings then, may be bought at the expense of expertise and reliability.


7.2-5 Comprehensibility

It is not simply 'technicians' who consider traffic forecasts and since forecasting can make no pretence to being an exact science, many lay people, usually those affected by the implied implications of the forecasts, may wish to consider the validity of the forecasting methods employed. The forecasting methods must appear consistent with the other elements of the transport planning exercise, and not be simply self-fulfilling prophecies. (Of course, the opposite may be desired by the policy-makers.) There are, however, potential problems. The extrapolative methods of forecasting car ownership employed in the appraisal of inter-urban road investment, for instance, were relatively straightforward to understand and, in consequence, came under severe public scrutiny. (21) The criticisms were so vocal that in 1975 traffic forecasts were deemed "matters of policy" and placed outside of appraisal at public enquiries. (22) Inspectors at public enquiries were duly told not to permit questioning of any traffic forecasts. Such measures, however, proved extremely unpopular and it is possibly less damaging to explicitly indicate the implicit judgements made in modelling and the inherent weaknesses in any forecasting methodology rather than present forecasts as scientific and unquestionable facts. A practical difficulty is still likely to arise, however, as forecasting models become more technical and their output less easily


22. A letter from the Council on Tribunals in August 1975 stated explicitly:-
"It appears that the D.o.E. memorandum H3/75 (National Traffic Forecasts) is one of a series of technical memoranda which lay down design standards and assumptions to be used by the Department in drawing up road proposals. The Department regards these as matters of policy" (writer's italics).
understood (e.g. discrete choice models yield probabilities while interactive models have a relatively high 'qualitative' element).
As with many other aspects of transport appraisal, there may be important trade-offs which have to be made, in this case between the accuracy or cost of forecasts and the public's willingness to accept their validity.

7.2-6 Form of Output

Normally forecasts yield, say, the future level of per capita car ownership or the distribution of trips between origin-destination pairs but in practice different approaches tend to offer different forms of forecast output. In some cases this is unimportant or simple conversion factors may be applied but this is far from the normal situation. The early extrapolative models of car ownership produced expected average per capita ownership predictions which at that time ideally suited the needs of those concerned with appraising trunk road investment and continued to provide suitable inputs when COBA, a computerised procedure employed to appraise small-scale road schemes, was introduced. (23) Such forecasts are of much less use at the local level where an entire local network comes under scrutiny. Here forecasts of non-car, one-car and multi-car owning households are often thought more useful since it is this trichotomy which is important in determining future travel patterns. Attempts to apply conversion

factors to the per capita forecasts have been made but this complicates the forecasting process and introduces the possibility of a compounding of forecasting errors.

The form of prediction provided by one sub-model in the overall traffic forecasting exercise must dovetail into that which follows it. It must be remembered that the demand for car ownership is derived from the demand for its use which in turn is derived from the demand to be at or reach some final destination. One of the current difficulties in car ownership forecasting is that while there have been considerable efforts made to improve this stage in the overall traffic forecasting exercise, the car use models tend to remain rather basic and do not easily accommodate the probabilistic predictions provided by causal ownership models. At a higher level of abstraction, the underlying assumptions of many existing traffic forecasting methods conflict with recent developments in appraisal techniques. Much of the current philosophy underlying transport analysis is now based not upon the classical assumptions of maximisation but rather upon notions satisficing - ideas of employing multi-criteria project appraisal techniques are now being assimilated into official transport decision-making. For internal consistency within the overall appraisal process, therefore, there is a need for the output produced by the traffic forecasts to be compatible with the implied behaviour assumptions underlying the complete appraisal methodology. The


25. For an account of recent developments in public sector transport decision-making see Appendix 5.
need to revise car ownership forecasting models in this way was highlighted by Pearman and Button \(^{(26)}\) and is implicit in Dix's \(^{(27)}\) advocacy of interactive forecasting models (see below) when he argues for "behavioural realism" and an emphasis on "understanding the phenomenon".

What is quite clear when considering these various qualities which are sought from traffic forecasting models are that many of them are mutually exclusive or, at best, major trade-offs have to be made between the extent to which the different attributes desired may be achieved. This is why in practical terms, it is important to be extremely clear about the exact way forecasts are going to be used and to establish from this the relative importance which should be attached to each of the qualities outlined above. It is interesting to note that over time 'fashions' in forecasting have changed and the importance attached to the various attributes of different forecasting methods have fluctuated in the eyes of the analyst. In particular, at the local, urban level as financial constraints have tightened economy has become a prime consideration and now far more care is taken over the basic data collection exercise than a decade or more ago. Similarly, since many of the parameters formerly thought to be relatively stable over time, or possibly changing in a steady, readily discernible way, can no longer be taken as given, the fore-

\(^{26}\) Pearman and Button (1981), op. cit.

casting exercise also has become part of the learning process with forecasting models serving the dual role of predicting and increasing our understanding of the basic, underlying influence on travel behaviour.

To what extent do the various approaches to car ownership forecasting meet these requirements? Table 7.1 gives a very general breakdown of the modelling and forecasting techniques available together with details about possible refinements, and an assessment of their relative pros and cons. All the techniques, with the exception of the Interactive or Activity Analysis framework, have been discussed in Chapter 3, in terms of their technical attributes.

Activity analysis, since it does appear in the table and also because it is currently attracting some research efforts, justifies a brief digression. It is not strictly a forecasting model and has yet to be fully developed in the car ownership context. It is essentially an approach to data analysis and response assessment. Activity analysis represents an attempt to move away from the mathematical basis of the conventional approaches to forecasting where mathematical convenience has often been given priority over a thorough appreciation of why traffic patterns emerge. In particular, the aim is to produce a forecasting framework which gets close to the essential decision process underlying household travel behaviour. Rather than, for instance, just incorporating a variable such as household status within a mathematical format because it is statistically significant, interactive modelling seeks to explain why status affects travel behaviour and to make use of this understanding in the forecasting of

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<table>
<thead>
<tr>
<th>DESCRIPTIVE</th>
<th>FEATURES</th>
<th>EXAMPLE</th>
<th>REFINEMENTS</th>
<th>ADVANTAGES</th>
<th>LIMITATIONS</th>
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<tr>
<td>NODAL</td>
<td>(1) based on product life cycle theory</td>
<td>Tanner (1973)</td>
<td>(4) Incorporation of additional socio-economic variables (Tanner, 1975)</td>
<td>(1) cheap and easy to calibrate</td>
<td>(1) small policy sensitivity in its basic form</td>
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<td>(2) Time series data</td>
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<td>(5) Use of more sophisticated growth patterns (Tanner, 1978)</td>
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<td>(2) intractable use of past traffic holding in the future</td>
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<td>(3) Formally a non-linear</td>
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<td>(6) Introduction of lumped effects (Tanner, 1979)</td>
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<td>(7) Likely to be sensitive to the anticipation level employed</td>
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<td>(8) Formally highly aggregated</td>
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<td>(9) Produces deterministic forecast</td>
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<td>(10) Calibrated using a variety of point fitting and regression techniques</td>
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<td>(11) Valid for long term forecasting</td>
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<td>STRUCTURE</td>
<td>(1) Source of regional or sub-regional traffic</td>
<td>Regional (1970)</td>
<td>(12) lower levels of central aggregation (Button, 1973)</td>
<td>(13) Does not require specialized computer software</td>
<td>(14) Assumes intra-regional structure will hold in the future</td>
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<td>(2) Source of regional or sub-regional traffic flow</td>
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<td>(15) Energy balance &amp; range of socio-economic variables</td>
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<td>(16) Use for school and non-work related large scale models</td>
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<td>(3) Based on aggregated, ratio socio-economic variables</td>
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<td>(16) Relatively simple to transform variables</td>
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<td>(4) Usually calibrating simple equation regression techniques</td>
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<td>(5) Mass transit oriented data or public survey data</td>
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<td>(6) Data collected at regional or urban level</td>
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<td>(9) Very limited to examine car stock</td>
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<td>(10) Use new socio-economic data</td>
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<td>(11) Used extensively on socio-economic data</td>
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<td>(12) Distinguish between new and replacement demand</td>
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<td>(13) Change in socio-economic variables</td>
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<td>(14) Price of car</td>
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**Table 7.1**

An Overview of Car Ownership Forecasting Techniques
future travel behaviour. To date the approach has only been applied in small-scale studies mainly because of the specialised data collecting techniques required. (28)

Ideally an interactive model should exhibit a number of properties:-

- It should involve the entire households and allow for interactions between their members
- It should make existing constraints on household behaviour specific
- It should start from the households' existing pattern of behaviour
- It should work by confronting households with realistic changes in their travel environment and allow them to respond realistically
- It should allow for the influence of long-term adaptation
- It should be able to tell the investigator something fundamental that he did not know before.

Some of the practical difficulties in meeting these requirements are highlighted in the work of the Oxford University Transport Study


29. Heggie, op. cit.
Unit and the 'household activities travel simulator' (HATS) which it developed. This forecasting procedure presents a small sample of households (usually stratified to reflect the socio-economic composition of the local population) with a board showing a map of the surrounding area combined with a 24-hour 'strip representation of coloured pieces' reflecting how current activities of each household are spread over space and throughout the day. The various transport investment options (including the do-nothing state) are postulated and the effect on the different households' activities throughout the day and over space are simulated by adjustments to the strip representation. In this way, changes brought about in the transport system after investment may be seen to influence the entire 24-hour life pattern of each household and, apparently unsuspected changes in 'remote' trip-making behaviour can be traced back to the investment. Theoretically, it should permit the modeller to tell whether car ownership is probable or not. The emphasis, by being focused on the micro-unit, should permit much clearer insights into the overall, long-term affects on travel patterns of transport investments.

The difficulties besides the costs, are that while the approach embraces interactions within households it is less certain that it predicts the consequences of interactions between households. Each household will almost inevitably assume that those it interacts with (e.g. in terms of social meetings, co-ordinating school trips, etc.) will retain their existing travel patterns or make guesses about how it will adapt to the investment. In the long term, of course, the various changes in the travel behaviour of individual households will, due to experience, adapt to those of their neighbours. The adoption
of Delphi type procedures may offer a method of coping with this problem but only at the cost of more interviewing and greater complexity.

Returning to Table 7.1, and the practical usefulness of the various car ownership forecasting techniques, it is possibly helpful to consider the pros and cons of the alternatives (excluding the Interactive Approach which has not to date been fully developed) under three broad headings:

(a) The Extrapolative School. As we have seen, models under this general grouping forecast by assuming, sometimes with slight modification, that an existing time trend continues into the future. In the car ownership context the practical problems involve making the forecasts policy sensitive without considerably complicating and modifying the intrinsically simple and easily understood methodology. Additionally, where so-called policy-sensitive factors have been included in an extrapolative framework, they have tended to be of a 'macro' nature reflecting influences such as changes in fuel taxation rather than of a planning nature. The introduction of policy sensitivity into the TRRL national forecasting model has also led to extremely wide bands of projections being made which have posed problems for those using the forecasts. At the national, if not the local, level the extrapolative approach does, however, offer useful back up and relatively robust forecasts to support more sophisticated modelling frameworks.
(b) The Planning School. This may be seen to embrace the purely pragmatic models such as the stock-adjustment, spatially aggregated econometric models and category analysis. Although there is some underlying economic theory behind these types of model it is generally far removed and little concerned with consumer theory. The lineage of these models can be traced back to transportation/land-use planning philosophies of the 1960s when there was no real necessity to have a full understanding of the transport market provided reasonable forecasts were produced. Similarly, relatively abundant funds did not necessitate economy in data collection. Although, therefore, models from the planning school can be adopted to take disaggregate household data they are really aggregate models and attempts to modify them tend to both increase the problems of calibration and the complexity of forecasting. In their cross-sectional forms they also require a substantial input of data to ensure that their error dispersions around the aggregate means reduce to a statistically acceptable level. This emphasis on the zone as the basic unit of study is useful in terms of technical design of transport facilities but considerably reduces the efficiency of forecasting models.

(c) The Causal School. Causal models offer an approach based in modern economic theory although its application in practical modelling does require the adoption of rather stringent assumptions at present. The theoretical strengths of the methodology is somewhat tempered by the need at present to rely upon cross-sectional data sources and the difficulties of predicting the future path of some of the key independent variables. The output produced from car ownership models is in a form consistent with other sub-models of modern transport.
demand modelling but is not easily understood or appreciated by many non-technical policy-makers unless presented with considerable care.

Overall it is quite clear that just as the different modelling and forecasting techniques have technical strengths and weaknesses so they have comparable practical strengths and weaknesses. It is not altogether clear, however, that one has to accept theoretical weakness to overcome the practical difficulties of application. The disaggregate, discrete choice approach, even where it is necessary to assume linear additive utility functions to permit the application of multi-nomial logit modelling, does offer a framework with a moderately solid theoretical foundation and certain practical advantages. Its main weakness, in fact, at present seems to be the rather-complex way in which results and forecasts are presented but is not an insurmountable difficulty.

7.3 Directions for Future Research

This thesis has limited itself to considering a small number of issues; it can in no way be seen as offering a comprehensive account of how economic theory and ideas may improve transport modelling and forecasting. There are still many areas left which require further study and research. In the context of car ownership, which has been the major topic of this work, the areas deserving particular attention may be identified as relating either to inadequacies in our understanding of household behaviour, or of the interdependencies between the variables of relevance to car ownership decisions.
There is no escaping the fact that our present theoretical understanding of the way in which car ownership fits into the economic and general behaviour decisions of households is inadequate. Equally, adequate data against which to assess theoretical constraints is rare. It is particularly clear that our understanding of the actual functioning of the car market needs strengthening. Specifically, there is the need for further research into the dynamic aspects of its operations especially in the way that shocks to the market (e.g. higher petrol prices) work their way through the prices of secondhand cars and smaller cars to influence the overall cost of motoring.\(^{(30)}\) The company car market is equally poorly understood, especially with respect to its influence on the 'second car' ownership level and its impact on the secondhand car market.

On the demand side, our understanding of the decision processes and the motivations of households at which the switch from being non-car owning to become car owning or move from single ownership to multiple ownership is extremely difficult. At present nearly all models, including those developed here, attempt to model the incidence of ownership and are, thus, one step removed from the real influences on behaviour. A practical problem here is that data collection at the margin (i.e. those households at the point of moving between household car owning categories) is scant and extremely difficult - not to say expensive - to collect. Questioning owners or non-owners once a decision has been made results in imperfections of memory recall and,

\(^{(30)}\) Although there has been limited work in this field (e.g. by M.J.H. Mogridge: The effect of the oil crisis on the growth in the ownership of and use of cars, Transportation, Vol.7, 1978, pp.45-65) this has tended to be based on rather poor data and at a high level of aggregation.
in some cases, a degree of \textit{ex post} rationalisation. The moves by Hensher\textsuperscript{(31)} in Australia to set up a panel sample to collect longitudinal data related to travel demand offers one method of circumventing some of these problems although the infrequency of questioning is still likely to distort the information extracted to some extent. It would at least provide additional evidence on the stability over time of relationships which, at present, have to be estimated from often isolated and, frequently, poor matched series of cross-sectional sources.

The question of simultaneous modelling, although explored in Chapter 5, is still not completely resolved. The model we develop here, although offering unbiased parameters, still leaves open the technical questions of efficiency and of improved specification.\textsuperscript{(32)}

The interrelationship between decisions regarding car ownership and car use still requires a considerable research effort, particularly since there is increasing evidence that decisions regarding, for example, mode choice are more closely related to car ownership than the more conventional generalised cost variables.\textsuperscript{(33)}

32. Pearman and Button (1981), op. cit., suggest that one possible pragmatic interim compromise which could be employed while more intellectually satisfying disaggregate simultaneous models are developed, is to make use of aggregate parameters (e.g. elasticities) in certain of the household-based equations in the system. Such knowledge of specific parameters has already been obtained in zonal level studies, where the problem of a discrete dependent car ownership variable does not arise; see, for instance, S.R. Jones and J.C. Tanner: \textit{Car Ownership and Public Transport}, Transport and Road Research Laboratory Supplementary Report 464, 1979.
this is the question of how decisions are made within the increasing number of multi-car households regarding the use of the 'first' car and the 'second' car - a distinction which poses problems of its own. As transport costs rise it will also become increasingly important to understand car use in relation to job choice and residential location.
APPENDIX 1

MOTOR CAR OWNERSHIP IN THE WEST RIDING OF YORKSHIRE (1)

All. Introduction

The empirical work undertaken is, in many ways, an extension of that carried out by Buxton and Rhys, (2) especially in as far as we concentrate on isolating the prime determinants of areal disparities in car-ownership by using linear regression techniques. It differs from their work in that greater emphasis is placed upon the role played by various socio-economic indices; this partly results from constraints inherent in the data but, at the same time, it is felt that these indices reflect fairly adequately the influences of several of the traditional planning variables. A second difference is that the analysis is performed at the local authority and ward, rather than county, level; any loss this entails in terms of the forced omission of variables is compensated for by the greater disaggregation it allows. (3) A further sacrifice, necessitated by practical considerations, is that the area covered by the analysis is relatively small.


3. In attempting to construct an initial sampling frame, C. Holmes (Construction and stratification of a sample frame of primary sampling units, The Statistician, Vol.18, 1969, pp.163-185) argues that a local authority area is more homogeneous than even a constituency (excluding the large pre-1972 county boroughs) but we suggest that the disaggregation can be taken further by considering wards and parishes.
Al.2 The Data

The region selected for analysis is the West Riding of Yorkshire. It is not claimed that this, in any way, represents a 'typical county' - if anything, quite the reverse - but its physical size, combined with its diversity of geographical and socio-economic conditions, does offer, albeit a rather inadequate, microcosm of the country as a whole. The statistics used are extracted from the County Report for the West Riding (4) and from computerised data sheets supplied to local authorities; all the original information coming from the 1966 Sample Census. This source offers data with the minimum of zonal aggregation, whilst retaining sufficient detail to allow analysis by regression techniques. A stepwise procedure is adopted to ensure that variables superfluous to the explanation provided by the models are omitted. (5) An additional point to note is that a constant term is always forced into the equations regardless of its associated standard error; this is done on the principle that it is safer to incorporate a constant than to ignore it unless there are sound theoretical reasons for taking the latter course. (6)

The variables used in this study are:

Car-Ownership (C.O.) This is the dependent variable throughout and represents the percentage of households in each local authority, and later, ward which own at least one car or private van. The


5. The programme used being the I.C.L. 1900 series, Statistical Analysis System Mark 2 applications package.

variable implicitly assumes the household to be the basic behavioural unit and hence provides the opportunity to test certain hypothesis concerning the influence of household size on vehicle ownership.

The variable contrasts with that used in the majority of past studies which have taken the individual to be the car purchasing unit; this, however, tends to conflict with the family nature of the good. In a number of instances, we resort to cars per 1,000 persons for illustrative purposes and denote this by the superscript 'I'; similarly, if we discuss the number of vehicles owned, this is shown by a subscript indicating that number.

Persons per Household (P.H.) This is simply the average number of persons living in a household.

Economically Active (E.A.) This variable gives the percentage of males aged over fifteen who are either actively employed or seeking employment. It is included because their upbringing in a non-car orientated society may be expected to have some psychological effect on elderly, and so retired, people, which reduces their car-owning potential. In addition, it enables us to allow for disabled people who are less likely to be car-owners.

Social Structure (S.S.) This represents the social composition of each local authority area and ward by defining the percentage of males who are classified as employers, managers or having professional status by the Registrar General's social and economic grouping scheme (the categories being selected are 1, 2, 3, 4 and 13).

Household Ownership (H.O.) This gives the percentage of householders who own their homes.

Population Density (P.D.) This represents the number of persons living on an acre of land in each local authority and ward. As the variable represents some measure of accessibility or "ease of interaction", it was decided to base it upon individuals rather than households as the former are the main determinants of the level of congestion and the adequacy of local public transport provision.

The list shows an obvious omission: namely, some measure of household income. Time series studies of national car-ownership patterns have usually included such a variable and have, indeed, generally found it to be significant. In addition, a great deal of contemporary work in applied econometrics is concerned with the estimation of income elasticities of demand for consumer durables, and especially for motor vehicles, over various time periods. The role of income in cross-sectional work is not so obvious, however. In several of their regressions, Buxton and Rhys found their income variable insignificant; an experience that they share with Fishwick. There may be several reasons for these results.


It is probably true that income exerts a fairly strong influence on the sale of new vehicles but that, due to the existence of a sophisticated hierarchy of second-hand car markets, it may be less important in determining the areal distribution of the vehicle stock, most people being able to offset their income differential by dealing in markets specialising in older, and therefore cheaper, cars. Income may be more important in deciding the number of cars a family owns, but our analysis is mainly based upon a binary classification and so this is only going to be relevant in a limited number of the earlier regressions. Using tabular analysis, Sleeman concluded that although income may affect the regional dispersion of motor vehicle ownership, it has no influence within such areas - urban/rural disparities being far more important - implying that the role of income in discrete areas is minimal.

In addition, income may be introduced into the model indirectly if it is sufficiently correlated with other variables. Earlier studies have shown income to be closely related to population density and intuitively it also seems likely to show a high degree of correlation with both social status and household ownership. Hence, although one would ideally like to include some explicit income effects, its omission need not unduly affect the analysis.


12. For example, Fishwick, op. cit.
A1.3 Results

A1.3-1 Local Authority Areas

Initially, several arithmetic-linear and logarithmic-linear (i.e. with all variables expressed as their natural logarithms) regressions were performed on data taken directly from the County Report for the West Riding. This has the effect of limiting the analysis to local authority areas with populations exceeding 15,000 which clearly, due to the omission of the smaller authorities, will introduce some bias into the results. However, these tabulations do have the advantage that they allow analysis of car-ownership at the individual level without requiring considerable effort in extracting data from the more detailed reports we consider later. The regressions also allow a few simple comparisons to be made between the results obtained for the West Riding and those of Fishwick and Buxton and Rhys.

The stepwise procedure which is adopted excludes all but the social status and population density variables from the models; others being insignificant at the 5% level. As we see in the results set out below, the models offer extremely good fits and there is little to choose between the explanations supplied; the linear one being marginally superior.

$$C.O. = 93.1846 + 5.2223 \text{ S.S.} - 2.7207 \text{ P.D.}$$

$$\begin{align*}
(0.2313) & \quad (0.3801) \\
R^2 &= 92.16\% \\ 
\end{align*}$$

$$\log e C.O. = 4.0595 + 0.4077 \log e \text{ S.S.} - 0.0803 \log e \text{ P.D.}$$

$$\begin{align*}
(0.0216) & \quad (0.0107) \\
R^2 &= 90.82\% \\ 
\end{align*}$$

The coefficients take the signs generally associated with them; car-ownership showing a strong positive relationship with social structure and an inverse relationship with population density.
In this and another respect, the results are similar to those obtained by Buxton and Rhys; the second similarity being the dominant constant term. The magnitude of the constant term is disquieting as the coefficient represents the mean effect of the excluded sub-population of variables.

In an attempt to improve the fit, an additional transformation was explored; this being the sigmoid type function obtained from a 'quasi-logistic' curve. This differs from the true logistic curve in that it has power functions rather than exponentials (i.e. the traditional logistic curve is $Y = e^{c+bX}/(1+e^{c+bX})$ but the quasi-logistic formulation is $Y = e^{cX^b}/(1+e^{cX^b})$ where $Y$ is the dependent variable, $X$ the independent variable and $c$ and $b$ are the parameters to be calculated). In some respects, the quasi-logistic curve resembles the equation employed in 'logit analysis' but its calibration takes no account of the distribution of error terms. The results obtained using this format offer an explanation comparable to that supplied by the double-logarithmic transformation but is not superior to it; a reflection perhaps of the limited range of ownership levels which are being considered.

\[
\log_{10} \left[ \frac{C.O.}{1-C.O.} \right] = -2.28386 + 0.4776 \log_{10} S.S. - 0.0965 \log_{10} P.D. \\
\text{ (0.0257)} \quad \text{ (0.0126)} \quad R^2 = 90.82\% \quad \text{Eq. A1.3}
\]

The use of cars per 1,000 population is far from ideal. The car is basically a family good and the economies derived from its


purchase increase considerably as average occupancy rate increases; a feature of motor travel being that, unlike public transport, journey costs per person fall as the number of travellers rises.

Before we leave the County Report data, one other set of calculations were made concerning the influences affecting the rates of single and multi-car ownership between families. The equations obtained from the simple linear model are (16)

\[
C.O. 1 = 32.0307 + 0.5553 \text{ S.S.} - 0.9417 \text{ P.D.} \\
(0.0998) \quad (0.1640) \\
R^2 = 59.75\% \quad \text{Eq.A1.4}
\]

\[
C.O. 2 = -10.4676 + 3.3559 \text{ P.H.} + 0.4292 \text{ S.S.} - 0.1058 \text{ P.D.} \\
(0.7764) \quad (0.0262) \quad (0.0392) \\
R^2 = 86.49\% \quad \text{Eq.A1.5}
\]

It is apparent that the variables at our disposal are more important in explaining between local authority variations in the percentage of multi-car households than they are in explaining variations in the percentages of single car-owning households. (Neither the double-logarithmic nor the quasi-logistic transformation improves on the simple linear model.) This phenomena is anticipated by the higher dispersion in the rates of single car ownership, the variance for \( C_2 \) being only 8.55% compared with 56.95% for \( C_1 \).

Despite the good fit obtained from these arithmetic linear models, there seems some justification for further modifications, especially the introduction of curvi-linear relationships for certain variables. The graphical presentation in Figs. A1.1 and A1.2 show a definite negative non-linear relationship between the dependent variables and population density (the graph only depicts

16. The regressions were performed throughout using 62 observations comprising 11 county boroughs, 40 urban districts and municipal boroughs and 11 rural districts.
observations taken from the rural districts and county boroughs for clarity but those from urban districts conform to the general pattern. (17) No clear impression emerged on the specification of the other variables so combinations of linear and semi-logarithmic relationships were tried. The best equations appear to be

\[
C.O.1 = -5.9323 + 7.9265 \text{ P.H.} + 8.4064 \log \text{ S.S.} - 3.010910 \log \text{ P.D.}
\]

\[
(3.8276) (1.6846) (0.7051)
\]

\[R^2 = 59.75\% \text{ Eq. Al. 6}\]

\[
C.O.2 = -8.5030 + 2.9070 \text{ P.H.} + 0.3998 \text{ S.S.} - 0.6411 \log \text{ P.D.}
\]

\[
(0.7225) (0.0256) (0.1456)
\]

\[R^2 = 88.55\% \text{ Eq. Al. 7}\]

The reformulated linear model for single car-ownership offers an identical \( R^2 \) to the arithmetic linear model but only does so at the expense of losing an additional degree of freedom. In contrast, the explanation offered by the new equation for multi-car ownership is superior to that offered by Equation Al.7 and the coefficients support many of the traditional theories about the demand for vehicle ownership. The semi-logarithmic population density relationship suggests that although the incentive to own a car falls as population density rises, it does so at an ever decreasing rate. The general negative slope of this relationship also indicates the likely importance of the variable in determining the ultimate saturation level of ownership. (18)

17. This is supported by the findings of P.W. Miller: - Car-ownership forecasting in Cardiff and Harlow, Car-Ownership Forecasting (P.T.R.C. Seminar Proceedings), 1970.

18. In densely populated Belgium, it has been claimed that a replacement market for cars has already been reached although the per capita ownership rate is only 0.25 cars. See, F.E.B.I.A.C.: - Rapport du Conseil D'Administration à L'Assemble Générale du 28 Avril, 1971. Allocution Prononcée pur M. Henri Daems President.
The bias created by restricting our analysis to local authorities with populations exceeding 15,000 may be removed by turning to the data made available in the reports produced of major statistics for each ward. If these are aggregated to the local authority area level, this allows smaller authorities to be included in the analysis; in fact, the number of observations rises from 62 to 96. Even so, some authorities were still omitted because of insufficient information on one or more variables; there is no reason, however, to suppose that they are in any way atypical.

The best arithmetic-linear and logarithmic-linear models developed from these statistics are

\[
\text{C.O.} = 21.8043 + 3.1834 \text{ P.H.} + 1.0846 \text{ S.S.} - 0.9922 \text{ P.D.} \\
(1.2706) \quad (0.0742) \quad (0.0130)
\]

\[R^2 = 80.28\% \text { Eq.A1.8}\]

\[
\log_e \text{C.O.} = 0.4288 + 0.5901 \log_e \text{EA} + 0.2910 \log_e \text{S.S.} - 0.0760 \log_e \text{P.D.} \\
(0.2819) \quad (0.0226) \quad (0.0086)
\]

\[R^2 = 80.46\% \text { Eq.A1.9}\]

(A quasi-logarithmic curve was also fitted and although this improved the coefficient of multiple determination slightly \(R^2 = 80.64\%\), it was only at the expense of including a high constant term and a perverse sign associated with the household ownership parameter.)

It is encouraging to note that both of these equations explain over 80% of the variation in car-ownership between local authorities despite the absence of a specific income variable. A marginally better fit is obtained for the data by combining original observations and logarithms.

\[
\text{C.O.} = 21.3269 + 3.1437 \text{ P.H.} + 1.1011 \text{ S.S.} - 3.1025 \log_e \text{P.D.} \\
(1.1926) \quad (0.0720) \quad (0.3496)
\]

\[R^2 = 86.63\% \text { Eq.A1.10}\]

The non-linear (effectively a negative semi-logarithmic) relationship
between the dependent variable and the population density variable is not surprising in view of our earlier findings. The specification for each variable emerges fairly clearly in Figs. A1.2 - A1.5 which plot each of them separately against the percentage of car-owning households in each area (although once again only the county borough and rural district observations are depicted for clarity). The household size and social status variates show a general linear pattern, whilst the accessibility proxy is quite clearly non-linear.

A1.3-2 Wards and Parishes

The aggregation inherent in local authority area models is still quite substantial, especially within the larger county boroughs which comprise the Central Yorkshire Conurbation. A series of modified regressions were performed to reduce this aggregation; these involved the use of ward and parish data. It proved impossible to use all of the Yorkshire ward and parish observations in a single equation due to limitations in computing capacity and so a stratified sample comprising of one-third of the observations was used initially; the stratification ensuring that each rural district, urban district and county borough was adequately represented. The models calibrated from this data were

\[
\begin{align*}
C.O. &= -5.3440 + 13.5046 \text{P.H.} + 0.5603 \text{S.S.} + 0.1752 \text{H.O.} - 0.7363 \text{P.D.} \\
&\quad (1.7898) \quad (0.0699) \quad (0.0434) \quad (0.0979) \\
R^2 &= 47.34\% \quad \text{Eq.A1.11}
\end{align*}
\]

\[
\begin{align*}
\log C.O. &= -1.1910 + 1.0085 \log \text{P.H.} + 0.7591 \log \text{E.A.} + 0.1160 \log \text{S.S.} \\
&\quad (0.3784) \quad (0.1007) \quad (0.0249) \\
&\quad + 0.0715 \log \text{H.O.} - 0.1104 \log \text{P.D.} \\
&\quad (0.0267) \quad (0.0287) \\
R^2 &= 33.40\% \quad \text{Eq.A1.12}
\end{align*}
\]

The regressions are based on a stratified sample selected from the
Figure A1.3

Percentage of Car-Owning Households

80%
70%
60%
50%
40%
30%
20%
10%

0 2.0 2.5 3.0 3.5 4.0 4.5
Household Size

- Rural Districts
- County Districts

2 Observations

Figure A1.4

Percentage of Car-Owning Households

80%
70%
60%
50%
40%
30%
20%
10%

0 10 20 30 40
Percentage of Males in Selected SEG Groups

- Rural Districts
- County Districts

2 Observations
Percentage of Car-Owning Households

80%
70%
60%
50%
40%
30%
20%
10%

Persons per Acre

0 2.5 5.0 7.5 10.0 12.5 15.0

Figure A1.5
total ward and parish population and consists of 313 observations. Clearly, the degree of explanation provided by these equations is inferior to that obtained from the local authority area statistics; we find that the $R^2$ values have fallen below the 50% level. Despite their poorer explanatory power, as indicated by the lower coefficients of multiple determination, the reduction in grouping suggests that the disaggregated regressions offer a more realistic picture of the underlying forces at work causing the geographical disparities in car-ownership.

The disaggregated regressions are less dependent upon their constant terms for their explanatory powers but at the same time retain their freedom from perverse coefficients (although the economically active variate, despite taking the anticipated positive sign when forced into the equation, makes no significant contribution to the simple linear model). The positive sign associated with the persons per household coefficient supports the common supposition that car-ownership becomes more practical, ceteris paribus, as family size increases; a result of the fall in average cost per person mile accompanying the higher car occupancy potential. As one would expect, the social status variable is highly significant and so confirms the view that members of the selected socio-economic groups have a high propensity to own a car. Similarly, household ownership is found to have a positive relationship with car-ownership and, although the link is not altogether clear, this is probably indicative of the tendency for owner-occupied houses to be situated in suburbs and dormitory districts where private transport is advantageous (the correlation
matrix reveals a degree of collinearity between the household ownership and population density variables but it does not appear to be sufficient to warrant the exclusion of either).

Population density has the anticipated negative coefficient for which a number of a priori arguments may be advanced. Densely populated areas tend to be near town and city centres where traffic congestion is high and public transport services are at their best. These forces tend to push up the generalised costs of private car travel versus other modes and so make vehicle ownership that much less attractive. In addition, these same areas supply shopping, recreational and employment facilities which keep the regular weekly travel of adjacent households to a minimum and this, coupled with the fall in the average cost per mile of motor travel as usage rises, tends to reduce the need for a car further. Despite these arguments, the multifarious nature of the variable makes it difficult to assign a specific causal significance to it; although this need not distract from its usefulness. It is one of the few variables found to be a major influence on car-ownership which is in some degree controllable by the planner and as such its potential role in policy-making should not be underestimated.

The level of disaggregation available in the statistics allows for a further modification; the analysis of variations in car-ownership between wards categorised by the type of local authority area in which they fall. This enables us, without having to resort to some more arbitrary division by population density levels, to assess the importance attached to the independent variables in several
environments and to see whether an effective trichotomy may be
drawn between car-ownership rates in cities, towns and country.
The data is divided according to whether the ward or, in country
areas, the parish, forms part of a rural district, urban district
(including municipal boroughs) or county borough. An initial
inspection of the resultant groups reveals, not surprisingly, that
the parishes tend to be far more sparsely populated than do either
category of ward; the greater difficulties of interaction generally
accompanying low levels of population density should therefore
encourage high car-ownership rates in parishes. This argument is
substantiated by the greater proportion of households found to own
cars in parishes (46.7%) compared with either the county borough
(33.8%) or urban district (38.6%) wards; in fact, whilst parishes
contain only 12.7% of the total households in the West Riding, they
contain 16% of those owning cars. The difference in ownership
rates between towns and conurbations is less distinct. (An
analysis of variance suggests (at the 5% confidence level) that
there is a significant difference in the three mean values but there
was too much data to allow any other comparisons.) It is also
apparent that the variation in ownership is far greater, both
relatively and absolutely, between parishes than it is between wards.
The standard deviation for parish observations was 24.78% with
Pearson's coefficient of variation taking a value of 43%; the
comparable figures for the urban district wards were 10.07% and
31% and for county borough wards were 11.74% and 31%.

The regressions performed on the categorised data, including
those where all of the variables are used, are shown in Table A1.1.\(^{19}\)

19. The regressions for rural districts are based upon 434 observations,
those for urban districts upon 335 observations and those for
county boroughs upon 169 observations.

309.
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<td>A1.13</td>
<td>R.D.</td>
<td>21.34%</td>
<td>16.7281</td>
<td>1.1788*</td>
<td>0.3225</td>
<td>0.3323</td>
<td>0.1638</td>
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<td>(0.0414)</td>
<td>(0.9566)</td>
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<td>R.D. Log.</td>
<td>25.61%</td>
<td>0.4786</td>
<td>0.4634*</td>
<td>0.4590</td>
<td>0.1548</td>
<td>0.1170</td>
<td>-0.1628</td>
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<td>(0.3385)</td>
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<td>R.D.</td>
<td>20.61%</td>
<td>18.0623</td>
<td>0.3618</td>
<td>0.3216</td>
<td>0.1539</td>
<td>-4.4746</td>
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<td>(0.0649)</td>
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<td>(0.0413)</td>
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<td>R.D. Log.</td>
<td>24.90%</td>
<td>0.8952</td>
<td>0.4937</td>
<td>0.1570</td>
<td>0.1103</td>
<td>-0.1430</td>
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<td>(0.0724)</td>
<td>(0.0248)</td>
<td>(0.0233)</td>
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<td>A1.17</td>
<td>U.D.</td>
<td>69.89%</td>
<td>-20.6632</td>
<td>15.2453</td>
<td>0.0744*</td>
<td>0.6267</td>
<td>0.3144</td>
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<td>(1.4509)</td>
<td>(0.0599)</td>
<td>(0.0510)</td>
<td>(0.0268)</td>
<td>(0.0464)</td>
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<tr>
<td>A1.18</td>
<td>U.D. Log.</td>
<td>45.16%</td>
<td>2.4348</td>
<td>0.9069</td>
<td>0.0502*</td>
<td>0.0787</td>
<td>0.1053</td>
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<td>(0.1606)</td>
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<td>A1.19</td>
<td>U.D.</td>
<td>69.72%</td>
<td>-25.8270</td>
<td>1.49438</td>
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<td>0.3070</td>
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<td>U.D. Log.</td>
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<td>2.2198</td>
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<td>0.0787</td>
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<td>(0.1523)</td>
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<td>(0.0125)</td>
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<td>A1.21</td>
<td>C.B.</td>
<td>78.68%</td>
<td>-26.7635</td>
<td>10.7505</td>
<td>0.1746</td>
<td>1.0419</td>
<td>0.0723</td>
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<td>(1.5502)</td>
<td>(0.0696)</td>
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<td>(0.0241)</td>
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<td>A1.22</td>
<td>C.B. Log.</td>
<td>71.91%</td>
<td>-0.8493</td>
<td>0.9583</td>
<td>0.5639</td>
<td>0.3662</td>
<td>0.0346*</td>
<td>-0.0224</td>
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<td>(0.1594)</td>
<td>(0.1916)</td>
<td>(0.0249)</td>
<td>(0.0220)</td>
<td>(0.0224)</td>
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<tr>
<td>A1.23</td>
<td>C.B. Log.</td>
<td>71.40%</td>
<td>-0.7666</td>
<td>0.9372</td>
<td>0.5692</td>
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<td>(0.1596)</td>
<td>(0.1934)</td>
<td>(0.0227)</td>
<td>(0.0224)</td>
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*Not statistically significant at 5% confidence level.

Table A1.1
It is immediately apparent that there are considerable differences in the level of explanation provided for each of the local authority types. In their simple linear forms, the models offer extremely good fits for both the county borough and urban district data, but there is a failure to explain some 75% of the variation in car-ownership between parishes. This poor explanation provided for rural areas is not altogether unexpected in view of the wider disparities in car-ownership which have to be explained. A further, and in some ways more important, point is that parishes tend to have smaller populations and so taking the mean values from such units is likely to involve far less averaging out than is commonly the case with wards which, in general, have far more inhabitants. The greater degree of aggregation involved in compiling their statistics tends to decrease the variations found between wards by increasing that within them and, as a consequence, it is possible that the total variation accounted for in models based upon such units is actually less than in those concerned with parishes.

A satisfying point to note, given the limitations of the analysis set out above, is that all of the regressions based upon disaggregated data contain logical coefficients even when they are not significant. We also find that both the social structure and population density variables retain a high degree of significance throughout - the former having the highest 't' statistic (the regression coefficient divided by its standard error) in all of the arithmetic-linear and the majority of the double-logarithmic models.

One final set of calculations was performed to see if the
specification of any of the models could be improved by re-running the regressions using combinations of the original observations, their reciprocals and their logarithms. In all cases improvements were found:

**Rural Districts**

\[
\text{C.O.} = -10.4334 + 17.7910 \log P.H. + 0.2917 \text{E.A.} + 0.2855 \text{S.S.} \\
(3.9540) \quad (0.0633) \quad (0.0528) \\
+ 0.2239 \log \text{H.O.} - 5.7001 \log \text{P.D.} \\
(0.0402) \quad (0.6983) \\
R^2 = 29.48\% \quad \text{Eq.A1.24}
\]

**Urban Districts**

\[
\text{C.O.} = -29.1734 + 45.8644 \log P.H. + 0.6474 \text{S.S.} + 0.2901 \text{H.O.} \\
(4.0681) \quad (0.04873) \quad (0.0254) \\
- 2.3830 \log \text{P.D.} \\
(0.3244) \\
R^2 = 70.90\% \quad \text{Eq.A1.25}
\]

**County Boroughs**

\[
\text{C.O.} = -70.3681 + 29.7364 \log P.H. + 13.7991 \log \text{E.A.} + 1.0341 \text{S.S.} \\
(4.4057) \quad (5.2406) \quad (0.0632) \\
+ 0.06436 \log \text{H.O.} - 1.6652 \log \text{P.D.} \\
(0.0235) \quad (0.6182) \\
R^2 = 78.85\% \quad \text{Eq.A1.26}
\]

The equations show a certain consistency in the form of response surface best suited to the explanatory variables. In all of the equations the persons per household and population density variables provide a superior explanation in the multivariable models when transformed into their natural logarithms. The straightforward linear form, however, proves more appropriate, other factors held constant, for the social structure and household ownership variates.

A similar exercise was performed using the information drawn
from the one-third stratified sample of all the wards and parishes,
and the best fitting equation was found to be:

$$C.O. = -21.0385 + 35.8288 \log P.H. + 3.5631 \log E.A. + 0.3855 S.S. + 0.2041 H.O. - 5.5697 \log P.D.$$

$$= 4.8004 (1.2859) (0.0610)$$

$$+ 0.3719$$

$$R^2 = 62.41\% \text{ Eq.A1.27}$$

Once again, we find a curvi-linear relationship between car-ownership and both household size and population density. The former suggests that the incentive to own a car increases with family size but that the increase tends to taper off as families get larger. The negative semi-logarithmic nature of the population density relationship confirms the impression given by the earlier equations on page that this variable is most influential in the less populous regions; as population density rises so car-ownership falls, other things remaining equal, but at a decreasing rate. This seems to support the widely held view that a fully urbanised society has some 'equilibrium' level of vehicle ownership.

A1.4 Conclusions

This case study has been limited throughout by restrictions imposed by the data and by the general magnitude of the task at hand but a number of interesting points have emerged. It has been shown that aggregation, even to the local authority area level, can obscure a great deal of the underlying influences on car-ownership variations which suggests that analysis of this phenomena should ideally be undertaken using data directly relating to the basic behavioural unit; preferably the household. Our empirical work has revealed a
dichotomy between urban and rural car-ownership patterns; the latter, resulting primarily from environmental factors, having the greater need for private transport. The difference between ownership rates in towns and cities is less distinct. These town/country differences can easily be overlooked if data is aggregated to the county level where averaging out tends to submerge the varying degree of urban-rural mix within each unit.

The regressions highlight the importance of household size as an explanatory variable and so confirm traditional economic arguments concerning the falling marginal cost of private motor vehicle travel associated with high occupancy potential. Similarly, the population density variate gives some indication of the influence of accessibility, although ideally specific measures of the various individual components of this complex proxy are needed before one can accurately assign exact causal links. Various types of accessibility indices are possible candidates for this role but they all require detailed data on the characteristics of the transportation network which are not immediately available. (20)

20. See Chapter 6, p.252.
A2.1 Introduction

In recent years there has been a continuing debate amongst transport planners as to the respective advantages of category analysis and multiple least-squares regression calibrated at the household level as techniques for forecasting future trip generation and car-ownership levels within the urban transportation modelling framework. Here, it is demonstrated that many of the main arguments employed in this controversy are incorrect (or, in some cases, simply irrelevant); that in certain instances and with specific model specifications, the alternatives reduce to the same thing (exhibiting a common set of advantages and weaknesses) and, finally, that there are a number of 'hybrid' models available which, following a number of conventional statistical tests to ensure the selection of the most appropriate specification, will yield more logical and reliable results. First, however, a brief summary of the two competing techniques.

A2.2 Multiple Regression and Category Analysis

Originally, single stage least-squares regression models of trip generation were calibrated at the geographic zone level of 1. This appendix draws heavily on K.J. Button: Category analysis and household multiple regression models of trip generation: a possible reconciliation, International Journal of Transport Economics, Vol.3, 1976, pp.19-27.
aggregation but following a number of comments by both American and British planners (2) about the statistical and logical difficulties this creates, the tendency now is to employ regression analysis at the household level. Similarly, it is argued that to ensure misleadingly good results are avoided, car-ownership should also be considered at the lowest level of aggregation consistent with the study in hand. Consequently, we concentrate on household-based models which, for most practical purposes, offers the superior level of aggregation.

The technique itself, which is widely used in the natural as well as social sciences, needs only a brief description. Couching our arguments in terms of trip generation analysis, the multiple regression technique usually relates the average number of trips a household undertakes \( T_i \) to a set of independent variables, generally some combination of household income, the occupation of the head of the household, family size, car-ownership level and access to public transport facilities (usually represented by a proxy such as residential density). If we denote these \( u \) independent variables as \( x_1, x_2, \ldots, x_u \) and assume simple linear relationship, then the regression model would take the form:

\[
T_i = a + b_1 x_{i1} + b_2 x_{i2} + \ldots + b_u x_{iu} + e
\]

where the parameters \( a, b_1, b_2, \ldots, b_u \) are estimated so that the (possibly weighted) sum of squares of deviations about the mean trip rate per household is minimised. Forecasting involves assuming these parameters remain constant over time and then feeding the estimated future values of the independent variables into the equation.

2. See Chapter 2, pp. 78-83.
The total number of trips for the study areas is found by aggregating across the households, i.e. \[ \sum_{i=1}^{K} T_i \] where there are K households in the area. (In some cases, total trips and aggregated independent variables have been employed directly but the obvious problem of zone size makes this unsatisfactory.)

Category analysis is a much more recent innovation coming initially from America. The usefulness of cross-classification procedures at the zoned level was quickly taken up by Taylor (3) at the Road Research Laboratory. It has subsequently been refined as a household-based trip generation model in the independent work of Wootton and Pick (4) and others in the United Kingdom and is now also widely used in car-ownership forecasting. Category analysis involves determining the average number of trips (or cars owned) by each of a set of categories or classes of household. Forecasting is possible by estimating the number of households which will fall into each category cell in the target year, multiplying these by the appropriate average car-ownership rate for that cell and then summing across cells. The technique is the same for trip generation, except that in this case the average number of trips made by houses falling into each category is assumed invariable over time.

Algebraically, if we define the number of households falling into each of m categories as \( Y_1, Y_2, \ldots, Y_m \) and, in a trip generation

model, the average number of trips undertaken by a household in each category as \(d_1, d_2, \ldots, d_m\), then the total number of trips generated in an area is:

\[
T = d_1 Y_1 + d_2 Y_2 + \ldots + d_m Y_m
\]

Eq. A2.2

It is worth noting that category analysis produces an estimate of future trip generation (or car-ownership) levels by directly aggregating across cells, whereas multiple regression requires the planner to sum across households. However, this point should not be held up as a significant difference between the approaches. It simply means that the order in which calculations are performed differs.

A2.3 The Use of Dummy Variables in Regression Analysis

Dichotomous variables are now widely used in regression analysis and have been frequently employed in both trip generation and car-ownership modelling. Used in a peculiar way, they can be employed in a regression to create a model identical to that of a category analysis. The dummies in such a model will correspond to the cells in the category approach, taking a value of unity if a household exhibits the characteristics of that cell and a zero otherwise. The specification of the model is of some importance since the introduction of dummies does not ipso facto turn a regression into a category analysis. Three conditions must first be met:

1. The regression equation must consist entirely of dummy independent variables.
(2) Each dummy variable must represent a single cell in the category analysis model. The importance of this can be demonstrated by taking the example of a two dimensional trip generation category analysis model with one dimension divided into three stratum, say $S_1$, $S_2$ and $S_3$ and the other into two stratum, $R_1$ and $R_2$. We may then form a category matrix with six cells, $x_1, x_2, ..., x_6$ taking the following shape:

<table>
<thead>
<tr>
<th></th>
<th>$S_1$</th>
<th>$S_2$</th>
<th>$S_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_1$</td>
<td>$(x_1)$</td>
<td>$(x_2)$</td>
<td>$(x_3)$</td>
</tr>
<tr>
<td>$R_2$</td>
<td>$(x_4)$</td>
<td>$(x_5)$</td>
<td>$(x_6)$</td>
</tr>
</tbody>
</table>

i.e., cell $x_1$ contains households exhibiting features $R_1$ and $S_1$, etc. The average household rates of trip-making per cell will be then represented as $b_1, b_2, ..., b_6$.

One will obtain identical results if one sums the individual household rates (i.e. $T = \sum_i T_i$) in the following regression model where each independent variable is a dummy identical to the cell specifications in the above category analysis (e.g. for any observation, $x_1$ will take the value 1 if a household has characteristics $S_1$ and $R_1$ and 0 otherwise). The model will therefore be:

$$T = b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_4 + b_5 x_5 + b_6 x_6 \quad \text{Eq. A2.3}$$

Any other dummy variable specification does not correspond directly to the category analysis approach.
If we take the following

\[ T = f_1 R_1 + f_2 R_2 + f_3 S_1 + f_4 S_2 + f_5 S_3 \]  

Eq. A2.4

where a household with characteristics \( R_1 \) and \( S_1 \) would record a 1 for both of these variables and 0 for the others. In this specification, the parameters are not cell means in the same sense as in category analysis.

(3) There must be no intercept term in the regression. It has been demonstrated by Suits\(^5\) that in order to calibrate a model containing dummies, it is necessary to either omit one dummy or else to leave out the intercept term. If the former is practised, the variable parameters remaining indicate the deviation in the trip generation rates of these categories from the average rate of the omitted category. The latter approach therefore circumvents the obvious problems associated with leaving out one dummy class and also more nearly meets condition (1) above.

A2.4 Comparisons of the Alternative Procedures

Perhaps the most frequently stated argument in support of the category analysis approach is its relative simplicity and the ease with which it may be interpreted. Simplicity, however, is only a virtue if the ultimate predictions produced by the model are the best and most reliable possible. In addition, since the parameters

of the dummy variable regression specified above are also cell means, simplicity is an equally valid ground for supporting this procedure.

Of more substance is the claim that category analysis circumvents the age-long statistical problem of specifying the correct response surface in the regression (e.g. should it be linear, log-linear, exponential or what?). In fact, the use of a dummy variable model serves exactly the same role; it is also neutral with respect to the response surface being assumed. Additionally, it has been demonstrated that the use of dummies can assist in removing some of the more troublesome problems encountered in the normal regression framework. In particular, Lewis (6) has shown that a dummy specification of certain variables may reduce the degree of multicollinearity, although care must be taken to ensure that a pound of flesh is not extracted by aggravating the homoskedasticity condition.

Just as the dummy variable model we have defined (Eq. A2.3) means that regressions of a certain specification may enjoy the same attributes as a category analysis, so it also suffers similar defects and shortcomings, although some econometricians have been reluctant to admit to this. Critics of category analysis have been quick to point to the difficulty of assessing the overall quality of such models and, in particular, the problems of verifying the usefulness of the category dimensions employed. (7)


The normal multiple regression model, on the other hand, furnishes a whole collection of summary measures indicating the quality or otherwise of the specification employed. It is implied in some writing that these tests may also be applied to the dummy variables specification outlined above and that, as a result, it is superior to the category analysis model. This, unfortunately, is not the case. If we take Equation A2.3 above, for example, it is neither possible to calculate a meaningful coefficient of multiple determination to test the fit of the entire equation nor to estimate the standard errors of individual variables. Taking the former by way of illustration, the omission of a constant term means that one cannot carry out the standard test of comparing the specification

\[ T = a + \sum_{j=1}^{6} b_j x_j \]

with the alternative \( T = a \) by means of a coefficient of determination. One may compare \( T = \sum_{j=1}^{6} b_j x_j \) with \( T = 0 \), but, as Pearman and Button (9) have shown, this has little to do with assessing the goodness-of-fit of the response surface.

A further advantage attributed to regression models is that they are less demanding on data. To obtain useful estimates of the average number of trips made or the cars owned, by each category of household, it is necessary to have a fairly large number of observations relating to households in the different categories. Since sampling is expensive, this pushes up the cost of carrying out a survey for the category analysis. On the other hand, it is claimed, regression is more economical because of the possibility of


interpolation. Again, this argument is invalid in the dummy variable specification which is directly comparable with category analysis. To obtain reasonable estimates of the \( b \) coefficients in Equation A2.3, it is necessary to have an adequate number of observations falling into each household type.

In summary, the multiple regression model which directly corresponds to a category analysis is neither superior to it nor inferior; it is exactly the same thing. Consequently, it becomes apparent that category analysis is nothing more than a specific specification of an all dummy variable multiple regression model. What the introduction of category analysis has done, however, is to have made transportation planners more aware of some of the shortcomings of the household regression approach to trip generation and car-ownership forecasting and to provide a foundation upon which a modification to the conventional linear model, which overcomes some of these limitations and failings, may be constructed.

A2.5 Hybrid Models

Attempts to incorporate the category analysis philosophy into least-squares multiple regression have usually taken the form of so-called hybrids. Essentially, these models have involved running multiple regressions, for either trip generation or car-ownership, on data for different categories of households. If we take as an example Burrell's (10) model of trip generation (which, in fact, relates

to individuals' behaviour rather than households but this does not affect the argument), we find trip-makers categorised according to their access to private transport and demographic characteristics. The trips made by those falling into each category are then regressed upon two further variables, income level and the residential density of the base zone. This, according to Burrell, "avoids both the artificial limitations of regression analysis and the empiricism of category analysis". A similar model has been tested using data collected in Risca and Ashford in Kent; in this case, households were stratified according to the cars owned and separated regressions of trip generation against income run on each.

In fact, these so-called hybrids - and models similar to them - are only a further example of special cases of multiple regression. Explicitly, these models are simply assuming that the slope and intercept terms in a regression calibrated on a set of continuous variables (such as income) vary according to the category of household under consideration (defined in terms of car-ownership, socio-economic peculiarities or whatever). The approach is, however, only one of a series of alternative situations. As alternatives, it is possible that only the intercept terms in the regression vary according to household category or it may be that it is only the slopes that differ. In both of these latter cases, separate regressions for each category is inappropriate - the model should incorporate dummy variables to allow for either differing


324.
slopes or intercepts. Deciding which of the three alternatives is appropriate—separate regressions, dummies for differing slopes or dummies for differing intercepts—is a relatively simple matter involving the application of analysis of variance procedures. However, although this procedure is well documented in the econometric literature, it is almost totally ignored by transport planners.

Perhaps the main advantage of the combined dummy variable/category analysis/regression approach is that it permits the logical combination of discrete and continuous variables. Category analysis demands that income and other naturally continuous variables are split into a number of statistically convenient but artificial classes or strata. By dividing households into categories according to discrete characteristics or by employing dummy variables, whichever is found to be appropriate, but keeping continuous variables in their original form, the planner is retaining the maximum realism and flexibility in his analysis. It also offers a much wider and more powerful range of statistical tests to assess the quality of the final model specification.

A2.6 Conclusions

This Appendix has attempted to bring together much of the recent debate concerning trip end and car-ownership forecasting techniques and to demonstrate that category analysis is only a very special case of multiple regression. Further, it has been illustrated that many of the arguments presented in the recent
debate have been erroneous or irrelevant. Finally, a logical outcome of these recent controversies is the combination of the category analysis approach with multiple regression. Such a synthesis permits tests of the quality of the final model and provides a much more realistic framework within which to incorporate the numerous influences on trip generation and car-ownership.
APPENDIX 3

A RE-EXAMINATION OF POST-WAR BRITISH CAR OWNERSHIP DATA

A3.1 The Extrapolative Model

The relative simplicity of the extrapolative method makes it possible to re-examine the data used by Tanner and to test the advantages of different model forms. This appendix concentrates, initially, on the underlying growth \( G_t \) on actual car ownership \( C_t \) and, in particular, looks at the evidence in favour of convexity in this plane and gets a feel for the saturation level parameters of the best fit lines. Various estimates of \( S \) are then used to examine the fit of different relationships in the \( C_t, t \) plane using data for the period 1953-1974. \( ^{3} \)

By looking at the \( G_t, C_t \) plane and testing for convexity/concavity, it is possible to assess the justification for using the power-growth function in the work of the TRRL in the late 1970s. The traditional logistic curve, it should be remembered, implies linearity in the \( G_t, C_t \) plane while the power growth function implies convexity. The calculations are made assuming initially that the underlying

1. This appendix draws heavily upon material contained in the author's article, K.J. Button, A.S. Fowkes and A.D. Pearman:- Disaggregate and aggregate car ownership forecasting in Great Britain, Transportation Research (Series A), Vol.14, 1980, pp.263-273.


3. This data is extracted from J.C. Tanner:- Forecasts of vehicles and traffic in Great Britain, Transport and Road Research Laboratory Report LR650, 1974.
forecasting model is purely extrapolative (i.e. solely dependent upon time) but then socio-economic factors are introduced to reflect the hybrid models later used in official forecasting.

Fowkes, Pearman and Button (4) tested a variety of curves in the $G_t$, $C_t$ plane. These ranged from curves so convex that they never reached saturation, through to the logistic (corresponding to a straight line) and, finally, to the form:

$$G_t = \alpha + \beta C_t^2$$

Eq. A3.1

which is concave to the origin, in the positive quadrant, when fitting predominantly downward sloping data. It was found, with the influences of incomes and motoring costs ignored, that the convex curves had lower $R^2$'s than the logistic. The logistic, however, in turn, proved to offer a poorer fit than the concave relationship specified in equation A3.1. The finding applied to both Great Britain as a whole and to each of the standard planning regions taken individually.

A3.2 The Introduction of Income

The exclusion of any allowance for income and motoring costs in this work, however, seriously weakens it. The inclusion of these influences changes the results considerably. We now compare the logistic curve, the quadratic (as specified in equation A3.1) and the Gompertz at the national level of aggregation. The Gompertz curve takes the form:

\[ G(t) = \alpha + e^{\beta t} \]

\[ G_t = \alpha + \beta \log_e C_t \] Eq. A3.2

in the \( G_t, C_t \) plane and is similar to the power growth function favoured by Tanner. It is convex in the \( G_t, C_t \) plane but has the same number of parameters as the logistic, one less than the power growth function.

Income variations are incorporated in four alternative ways:

(a) \( GY \) is the percentage growth rate of GDP over the previous year;
(b) \( RY \) is the deviation of the logarithm of GDP from an exponential trend line fitted for the period 1953-1974;
(c) \( RY1 \) is \( RY \) lagged 1 year;
(d) \( RY2 \) is \( RY \) lagged 2 years.

Motoring costs (\( RP \)) are also incorporated as deviations but no lag structures are considered. The trend equations employed are:

\[ TLY = 1819.4 + 9.42t \] Eq. A3.3
\[ TLP = 2131.7 - 6.62t \] Eq. A3.4

where \( TLY \) is one thousand times the trend of \( \log_{10} GDP \)

\( TLP \) is one thousand times the trend of the \( \log_{10} \) of Tanner's motoring cost index(15)

and \( t \) is a time trend with 1952 = 0.

Table A3.1 offers selected results of the regressions. The motoring cost variable has significant coefficients at the 5 per cent level and, therefore, its inclusion would seem to have improved the equations. The concave quadratic relationship ceases to offer the best fit following the introduction of this basic economic variable.

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>$\bar{R}^2$</th>
<th></th>
<th></th>
<th>Durbin-Watson Statistic</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Gompertz</td>
<td>Logistic</td>
<td>Quadratic</td>
<td>Gompertz</td>
<td>Logistic</td>
<td>Quadratic</td>
</tr>
<tr>
<td>None</td>
<td>0.530</td>
<td>0.587</td>
<td>0.610</td>
<td>1.19</td>
<td>1.34</td>
<td>1.41</td>
</tr>
<tr>
<td>RP</td>
<td>0.776</td>
<td>0.773</td>
<td>0.731</td>
<td>1.33</td>
<td>1.39</td>
<td>1.30</td>
</tr>
<tr>
<td>GY, RP</td>
<td>0.798</td>
<td>0.814</td>
<td>0.791</td>
<td>1.42</td>
<td>1.60</td>
<td>1.57</td>
</tr>
<tr>
<td>RY2, RP</td>
<td>0.824</td>
<td>0.826</td>
<td>0.795</td>
<td>1.51</td>
<td>1.60</td>
<td>1.49</td>
</tr>
</tbody>
</table>

Notes:  
(i) Variables as defined in text.  
(ii) $S^L$ is the implied saturation level using the logistic model in the $(G_t, C_t)$ plane.  
(iii) $R^2$ is the adjusted coefficient of determination.  
(iv) The Durbin-Watson test on the Durbin-Watson Statistic is inappropriate, but comparisons between the statistics for different equations are still meaningful.

Table A3.1
Comparative Results from Gompertz, Logistic and Quadratic Functions in the $G_t, C_t$ plane

Now the Gompertz relationship offers the highest $\bar{R}^2$ and the logistic the better Durbin-Watson statistics. There is also evidence in the final two rows that lagging income (which is significant at the 5 per cent level) improves the model fit further, a two period log appearing superior, and at the same time substantially improves the relative performance of the logistic curve. The final column of Table A3.1 indicates the implied saturation ($S^L$) level associated with the logistic model and it appears that the introduction of the lagged income effect does suggest saturation will be at a higher capita.
ownership level than that indicated by a straightforward $C_t$, $t$ relationship.

The strength of the logistic curve is also confirmed by regressions carried out in the $C_t$, $t$ plane. Three alternatives are examined, all based upon a logit transformation of $C_t$ regressed on a linear combination of trend, income and motoring costs. The transformation used is:

$$L = \log_e \left( \frac{C_t}{S - C_t} \right)$$

Eq. A3.5

where values of $S$ are prechosen in the range 0.26 (0.01) 0.45.

Analogously with the results found for the $G_t$, $C_t$ equations discussed above, three alternative forms are fitted:

'Log-logit'  $L = \alpha + \beta \, \text{LTLY}$

Eq. A3.6

'Logistic'  $L = \alpha + \beta \, \text{TLY}$

Eq. A3.7

'Exponential logit'  $L = \alpha + \beta \, \text{TY}$

Eq. A3.8

where $\text{TLY}$ is the trend of the logarithm of GDP as given in equation A3.3

$L\text{TLY}$ is the natural logarithm of TLY

and $\text{TY} = 10^{(\text{TLY}/1000)}$

The variables $R_Y$, $R_Y1$, $R_Y2$ and $R_P$ are also tested in various combinations. The data used is, once again, that for Great Britain (1953-1974).

The results of these regressions are set out in Table A3.2.

The first set of three equations is calibrated on the trend variable alone without income and motoring cost variables. In each case the
<table>
<thead>
<tr>
<th>Set</th>
<th>Variables included</th>
<th>$R^2$</th>
<th>Durbin-Watson</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>$\gamma$</th>
<th>$\hat{S}$</th>
<th>$\hat{S}^*$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>LTLY</td>
<td>0.9965</td>
<td>0.67*</td>
<td>-200.0621</td>
<td>26.4152*</td>
<td>-</td>
<td>0.34</td>
<td>0.46</td>
</tr>
<tr>
<td></td>
<td>TLY</td>
<td>0.9966</td>
<td>0.72*</td>
<td>-27.4036</td>
<td>0.0141*</td>
<td>-</td>
<td>0.33</td>
<td>0.42</td>
</tr>
<tr>
<td></td>
<td>TY</td>
<td>0.9967</td>
<td>1.03*</td>
<td>-7.1118</td>
<td>0.0845*</td>
<td>-</td>
<td>0.29</td>
<td>0.33</td>
</tr>
<tr>
<td>2</td>
<td>LTLY, RY</td>
<td>0.9983</td>
<td>1.15</td>
<td>-195.1357</td>
<td>25.7562*</td>
<td>0.0054*</td>
<td>0.35</td>
<td>0.43</td>
</tr>
<tr>
<td></td>
<td>TLY, RY</td>
<td>0.9983</td>
<td>1.19</td>
<td>-26.7099</td>
<td>0.0137*</td>
<td>0.0055*</td>
<td>0.34</td>
<td>0.40</td>
</tr>
<tr>
<td></td>
<td>TY, RY</td>
<td>0.9981</td>
<td>1.19</td>
<td>-7.1166</td>
<td>0.0845*</td>
<td>0.0057*</td>
<td>0.29</td>
<td>0.32</td>
</tr>
</tbody>
</table>

Notes: Notation as in text, dependent variable $\log_e \left( \frac{C_t}{S - C_t} \right)$.

* denotes significant at 5 per cent level.
Bracketed figures are standard errors.
$\alpha$ is constant term (no significance test performed).
$\beta$ is coefficient of the 'trend' variable.
$\gamma$ is coefficient of income residuals variable, RY.
$\hat{S}$ is the saturation level parameter of the best fit equation.
$\hat{S}^*$ is the lowest saturation level parameter of equations with at least twice the residual sum of squares of the equation reported, but above $\hat{S}$.

Table A3.2

Comparison of Log-Logit, Logistic and Exponential Logit Models

equation for the $S$ value which exhibits the greatest $R^2$ value is shown.
There is little difference in the goodness-of-fit although the exponential logit, corresponding to a concave curve in the $C_t, C_t$ plane is marginally superior. Since, however, the Durbin-Watson
test is appropriate in this case, it is clear there is significant auto-correlation of the residuals, indicating probably, missing variables or a wrong functional form. Set 2 of Table A3.2 shows the effect of incorporating the variable RY. The fit is markedly improved as is the Durbin-Watson statistic, which is just non-significant at the 5 per cent level. As with the equation examined in the $G_t, C_t$ plane, the 'concave' curve is no longer superior on the basis of $R^2$. The replacement of RY by the motoring cost variable, RP, does not improve the fit of any of the specifications, nor do the regression results suggest that the lagged income variable (RY1 or RY2) perform better than RY. Similarly, combining RP with any of the income variables has little effect, although it does raise $\hat{S}$ to about 0.38.

The results of this second set of calculations confirm those of Table A3.2, namely the incorporation of income and motoring cost variations removes the concavity in the $G_t, C_t$ plane as initially suggested by Fowkes, Pearman and Button. There is minimal evidence, though, to support the notion of convexity in this relationship, indeed the findings tend to support the logistic curve hypothesis. This is demonstrated by the $S$ of the best fit log-logit curve (equation A3.6) being (in Table A3.2) very close to the $S$ for the logistic curve (0.35 as against 0.34). The figures reported under $\hat{S}^+$ are the lowest saturation level (above $S$) of those equations with at least twice the residual sum of squared of the equation reported. This gives an indication of how inconsistent high $S$ values are with the data. If

6. Fowkes, Pearman and Button, op. cit.
a very long run analysis is adopted, it can be argued that convexity is present. (7) However, data from the very early years of the motor car may well be influenced by a technology replacement effect over and above those effects now operating, i.e. horse-drawn vehicles may have been replaced by motor vehicles.

The results presented in this appendix support the proposition that the growth path for cars per person should be sigmoid with a finite saturation level. The fact that projections of ownership using the logistic curve have, in the past, consistently tended to be too high suggests the possibility that a sigmoid curve convex, rather than linear, in the $C_t, C_s$ plane might be preferable. (8) However, the examination of post-war data for Great Britain presented here suggests that the over-predictions have been the result of inappropriate parameter estimations, not model form. Although back-projection would under-predict growth rates before the First World War, this may be explicable in terms of a technological transmission effect, operative at that time, over and above those effects still operative, i.e. horse-drawn vehicles were still competitive with motor vehicles.

7. See Tanner (1977), op. cit.

8. Tanner, loc. cit.
A4.1 Elementary Analysis by Medians

The method of analysis employed in this appendix is elementary analysis by medians. This is a simple data processing technique designed for preliminary analysis of information rather than hypothesis testing. The technique permits a simple breakdown of the effects of various independent variables on the dependent variable. It is used in the applied sciences but seldom employed in regional studies or by social scientists. An exception to this is the suggestion of Sen and Johnson\(^{(2)}\) that a related technique, elementary analysis by means, can prove a useful method of carrying out a preliminary screening of general transport survey data. The median procedure is, however, in some ways easier to apply, and hence is preferred here. The data, taken from the WYTCONSULT study of West Yorkshire,\(^{(3)}\) has also been subjected to an elementary analysis by means and the evidence is that there are no substantive differences in the results obtained by the two methods.

Elementary analysis by medians is useful because no complex calculations are necessary (indeed the calculations presented here

---

were undertaken without even the aid of a pocket calculator) and yet it produces useful insights into a data set which can assist in the specification of more detailed models. It has the advantage over other methods of data categorisation (e.g. the category analysis approach widely used in urban transport demand forecasting) that the problem of empty cells, which usually accompanies the high degree of multicollinearity often present in household data, can easily be circumvented. This latter feature did not prove relevant in this study but becomes important when categorisation is extended beyond two dimensions.

In brief, elementary analysis by medians is an iterative procedure which involves taking, in the case of a two dimensional matrix, successive medians from the rows and columns of the data. Two complete iterations, each by row and column, are normally sufficient to obtain acceptable results, although some minor adjustments may be required to produce the final table. The ultimate output is a breakdown of the original data matrix into four components:

(i) a common effect,
(ii) a vector of row effects,
(iii) a vector of column effects and
(iv) a matrix of residuals.

Summation of the common effect, the appropriate column and row effects together with an appropriate residual produces the original cell observation. Hence one can always return to the original category breakdown of the data. A full account of the necessary calculations is found in Tukey. (4) This paper is not intended to offer a

detailed account of the technique nor a critique of its usefulness
but rather concentrates on presenting and interpreting the results
of its application to the study of household car ownership patterns
in a large British conurbation.

It is important to emphasise, however, that elementary analysis
by medians is a method of breaking down data rather than a rigorous
statistical technique. It is a useful tool for examining trends in
data but cannot produce elasticities or other economic parameters.
The vector of row effects reflects, rather than quantifies, the extent
to which the vertical categorising variable influences car ownership.
Likewise, the vector of column effects serves a similar function for
the categorising variable on the horizontal. Examination of the
elements of these vectors can indicate the general explanatory power
of the categorising variables and the direction of the influences
exerted, but only in general terms. If, for example, the horizontal
categorisation is by household income groups in ascending order and
it is found, after applying elementary analysis by medians, that the
vector of column effects is also composed of elements in ascending
order than a positive relationship between income group and vehicle
ownership is suggested. The residual elements offer some guidance
to the overall fit of the model and the suitability of the underlying
specification. If the residuals are all relatively small, and
negative and positive signs are randomly scattered, then the variables
used for categorisation appears to be explaining much of the variation
in car ownership.
A4.2 The West Yorkshire Study

A frequently used proxy for public transport accessibility is a spatial variable reflecting the kind of geographical area in which a household is located. A variety of variables of this type (e.g. residential density, distance from the city centre, etc.) have been employed in transport studies with some success. The basic argument is that in densely populated parts of a city public transport provision is good, while, at the same time, due to congestion and limited parking facilities, the generalised cost of car travel is relatively high. Hence other things being equal, one would anticipate a positively sloped per capita car ownership gradient as one moves from densely populated urban areas to more sparsely populated suburbs. In this study, West Yorkshire is classified into three broad types of area - urban, dormitory, and rural/small towns - and variations in average car ownership levels between them is examined. Since household income is generally considered a dominant influence upon the purchase of consumer durables (although the exact specification of an appropriate income variable in the car purchasing content has been subject to some controversy), the effect of this variable was isolated by a second stratification of households by annual income. Eight income bands were defined, six with width of £1,030 and then £6,241-£7,800 with a residual of over £7,800 for completeness. Table A4.1(a) shows the average household car ownership level for each category of household.

5. See K.J. Button, A.D. Pearman and A.S. Fowkes:- Car Ownership Modelling and Forecasting (Gower Press, Aldershot), 1981, Chapter 5. See also Chapter 6, pp.228-242.
### Table A4.1(a)

<table>
<thead>
<tr>
<th>Zone type</th>
<th>Household income</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>£1041-£2080</td>
<td>£2081-£3120</td>
<td>£3121-£4160</td>
<td>£4161-£5200</td>
<td>£5201-£6240</td>
</tr>
<tr>
<td>Urban</td>
<td>0.07</td>
<td>0.25</td>
<td>0.55</td>
<td>0.68</td>
<td>0.84</td>
</tr>
<tr>
<td>Dormitory</td>
<td>0.15</td>
<td>0.53</td>
<td>0.80</td>
<td>1.03</td>
<td>1.41</td>
</tr>
<tr>
<td>Rural and small town</td>
<td>0.07</td>
<td>0.34</td>
<td>0.69</td>
<td>0.91</td>
<td>1.03</td>
</tr>
</tbody>
</table>

### Table A4.1(b)

<table>
<thead>
<tr>
<th>Zone type</th>
<th>Household income</th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>Row effect</th>
</tr>
</thead>
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<tr>
<td></td>
<td>£1041-£2080</td>
<td>£2081-£3120</td>
<td>£3121-£4160</td>
<td>£4161-£5200</td>
<td>£5201-£6240</td>
<td>£6241-£7800</td>
<td>&gt;£7800</td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td>0.21</td>
<td>0.09</td>
<td>0.07</td>
<td>0</td>
<td>0</td>
<td>-0.22</td>
<td>0</td>
<td>-0.13  -0.21</td>
</tr>
<tr>
<td>Dormitory</td>
<td>-0.08</td>
<td>0</td>
<td>-0.05</td>
<td>-0.02</td>
<td>0.20</td>
<td>0.11</td>
<td>-0.03</td>
<td>0.10   0.16</td>
</tr>
<tr>
<td>Rural and small town</td>
<td>0</td>
<td>-0.03</td>
<td>0</td>
<td>0.02</td>
<td>-0.02</td>
<td>0</td>
<td>0.11</td>
<td>0      0</td>
</tr>
<tr>
<td>Column effect</td>
<td>-0.90</td>
<td>-0.60</td>
<td>-0.28</td>
<td>-0.08</td>
<td>0.08</td>
<td>0.41</td>
<td>0.40</td>
<td>0.84   0.97</td>
</tr>
</tbody>
</table>

Certain trends are immediately apparent from Table A4.1(a) but these are clarified in Table A4.1(b) after the application of elementary analysis by medians. The consistent rise in the size of the column effect as income rises confirms the generally held view of a positive income effect on household car ownership levels. More interestingly, there is a marked difference in the size of the row effects suggesting, once income has been allowed for, distinct geo-
graphical variations in the propensity for households to own cars. Dormitory areas have comparatively high average ownership levels while the densely populated urban areas have much lower levels. Certainly, if more rigorous modelling is to be undertaken, there seems to be a case for constructing separate models for the various geographical areas if no more specific explanation of these differences is forthcoming. It suggests that, at the very least, a Chow test should be performed to see if these spatial variations are statistically significant.

The difficulty with geographical variables is that, although they may prove statistically useful in accounting for differences in car ownership levels, their exact causal influence is unclear and, at best, indirect. It is often stated that this type of variable is a surrogate for public transport provision but it is too general and insensitive to reflect accurately the impact of public transport on household car owners trip levels. At the policy-making level, it is impossible to isolate the effects of land-use planning and public transport policy options. Attempts have been made to construct explicit public transport quality indices and to assess their influence on local car ownership levels, but these have tended to be limited in scope. Fairhurst, (6) for example, examined the influence of frequency of bus services on car ownership in Greater London. The West Yorkshire study permits a more detailed index of public transport provision to be derived reflecting the generalised time cost of public transport in different areas. An index was constructed representing

the accessibility to work by public transport in each county strategic model zone in which the survey households were located. The index has four classes representing decreasing accessibility by public transport. Strictly the index represents differences in the generalised time cost of a typical journey to work for a household with no car available from the county strategic model zones containing the various households. We would expect, a priori, the index to be positively related to vehicle ownership if good public transport accessibility tends to discourage households from owning a car.

Table A4.2(a) presents the basic categorisation of households. Again the accessibility measure is combined with an income stratification, showing their respective average levels of car ownership. Table A4.2(b) reveals the results of applying elementary analysis by medians to the data. The consistent rise in the column effect, combined with the relatively large size of individual elements, indicates that the effect of household income remains both strong and positive.

More importantly, the increasing size of the elements in the row vector as one moves down the public transport index scale suggests an upward trend in average household car ownership as public transport generalised costs rise. There are no inconsistencies in the magnitude of the row effect values indicating a smooth positive relationship between the index and car ownership. The evidence is, therefore, and remembering the index is an inverse indicator of public transport accessibility, that good public transport may act to contain a substantial growth in average household car ownership levels.
### Table A4.2(a)

<table>
<thead>
<tr>
<th>Public transport accessibility</th>
<th>Household income</th>
<th>Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>£1041-£2080</td>
<td>£2081-£3120</td>
</tr>
<tr>
<td>1</td>
<td>0.07</td>
<td>0.24</td>
</tr>
<tr>
<td>2</td>
<td>0.06</td>
<td>0.30</td>
</tr>
<tr>
<td>3</td>
<td>0.07</td>
<td>0.37</td>
</tr>
<tr>
<td>4</td>
<td>0.10</td>
<td>0.37</td>
</tr>
</tbody>
</table>

### Table A4.2(b)

<table>
<thead>
<tr>
<th>Public transport accessibility</th>
<th>Household income</th>
<th>Row effect</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>£1041-£2080</td>
<td>£2081-£3120</td>
</tr>
<tr>
<td>1</td>
<td>0.16</td>
<td>0.06</td>
</tr>
<tr>
<td>2</td>
<td>0.04</td>
<td>0.01</td>
</tr>
<tr>
<td>3</td>
<td>-0.03</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>-0.08</td>
<td>-0.08</td>
</tr>
<tr>
<td>Column effect</td>
<td>-0.84</td>
<td>-0.57</td>
</tr>
</tbody>
</table>

### A4.3 Testing A Logit Specification

At the urban planning level it is important to know the breakdown of no-car, one-car and two or more car households since this influences household travel behaviour. Further, since recent changes in national transport policy emphasise the need to provide adequate
access for people without private transport, it is particularly important to isolate the characteristics of no-car households. Because of the dichotomous nature of the dependent variable in this type of analysis (a household either being a non-car owner or a car-owner) most econometric work in the field has tended to proceed in terms of transformations of the basic variables, and, since car ownership is often argued to be sigmoidally related to income, a logit framework of analysis is common. Although this is not strictly necessary when employing elementary analysis by medians, the fact that the technique is basically a screening device, usually employed prior to more rigorous analysis, suggests that logit transformations may usefully be examined since they are likely to be adopted in the forecasting context. In this case the proportion of households not owning a car in each cell was transformed into a logit (i.e. \( \ln \left( \frac{P_o}{1 - P_o} \right) \)). The resultant matrix of logits is presented as Table A4.3(a).

The subsequent application of elementary analysis by medians to this data set produced the results seen in Table A4.3(b). The residuals presented in the table are, in general, small compared to the column, row and common effects suggesting that the overall explanatory power of the public transport accessibility and household income variables is quite high. The negative effect of household income on the level of non-car ownership is also immediately apparent by the trend in the column effect. Additionally, we observe a negative relationship between the propensity for a household not to own a car and the generalised cost of local public transport services. The generally diagonal pattern of residuals, however, implies that the
Table A4.3(a)

<table>
<thead>
<tr>
<th>Public transport accessibility</th>
<th>Household income</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;£1041</td>
<td>£1041-£2080</td>
</tr>
<tr>
<td>1</td>
<td>2.65</td>
</tr>
<tr>
<td>2</td>
<td>2.82</td>
</tr>
<tr>
<td>3</td>
<td>2.92</td>
</tr>
<tr>
<td>4</td>
<td>2.51</td>
</tr>
</tbody>
</table>

Table A4.3(b)

<table>
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<tr>
<th>Public transport accessibility</th>
<th>Household income</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;£1041</td>
<td>£1041-£2080</td>
</tr>
<tr>
<td>1</td>
<td>-0.63</td>
</tr>
<tr>
<td>2</td>
<td>-0.13</td>
</tr>
<tr>
<td>3</td>
<td>0.29</td>
</tr>
<tr>
<td>4</td>
<td>0.12</td>
</tr>
</tbody>
</table>

Column effect | 3.88 | 1.91 | 0.76 | 0.18 | -0.18 | -0.60 | -1.24 | -1.82 | -1.09 |

Car ownership response of households to income changes is not identical in different accessibility bands. This, in conjunction with the relatively high residuals at extreme income levels, suggests the need in the later, more detailed, analysis for very careful choice of functional form possibly with quite different relations being fitted in some accessibility and income bands or that some additional variables need incorporation.
In conclusion, the West Yorkshire data suggest that the quality of local public transport does exert an influence both on average household car ownership levels and upon the decision of a household to become car owning. Households living in areas which have good access by public transport to work opportunities tend to both have a lower level of car ownership and to be less inclined to become car owning. Clearly, the method of analysis employed is not sufficiently rigorous to enable an assessment of the exact strength and nature of this influence but it does suggest that conventional approaches to car ownership forecasting based solely upon household characteristics are inadequate. It further suggests that the improvement of public transport provision by local transport agencies may be a useful tool in restricting car ownership growth (if this is felt to be a desirable policy objective) in urban areas.
APPENDIX 5

MODELS FOR DECISION-MAKING IN THE PUBLIC SECTOR

A5.1 Introduction

This appendix offers an account and explanation of the ways in which public sector decision-making has changed in the United Kingdom over the past twenty years. It is not directly couched in transport terms (although many of the illustrations are taken from the transport sector) but quite clearly, since the projections supplied by traffic forecasters are used by public sector transport decision-makers, the techniques are themselves per se of central importance.

The post-war period has witnessed a substantial growth in the public sector as government has deemed it desirable, for a variety of economic, social and political reasons, to play an increasing rôle in the provision of goods and services. Whereas at one time the meaning of economic efficiency was reasonably clear, the growth of an extensive public sector, where cost minimisation and profit maximisation are less compelling objectives, has led to the adoption of much wider concepts of efficiency. This does not mean that the financial considerations which play such an important rôle in private sector decision-making are entirely displaced, but rather that they are supplemented and modified by public sector undertakings to reflect a much wider and less tangible set of goals and objectives.

1. This appendix draws upon previous work by the author, viz:—
The extent to which public sector decision-making deviates from models of the private sector varies quite considerably between different areas of government involvement. Quite clearly, in some sectors, such as education, health, policy, defence and the provision of roads, the lack of a direct charging mechanism renders commercial criteria useless. At the other extreme, many of the nationalised industries operate in a market situation and, although controls are exercised to prevent monopoly exploitation, financial criteria have a very important function in decision-making. (2) As we see later, these differing features of public sector undertakings provide a useful method of categorisation when discussing decision-making frameworks.

The differing characteristics of public sector activities should not be taken as a reflection of differing objectives, rather they indicate differences in the constraints confronting the decision taken. The overriding objective which underlies all public sector decision-making is the maximisation of society's welfare but the varying characteristics and differing operational environments of the sector's undertakings present a complex of constraints which cover social, political and environmental considerations as well as those of a financial nature. Education and health, for example, are deemed to be 'merit goods' (3) for which no charge should be made, while the

2. The White Paper on the nationalised industries, for example, argues that, "An adequate level of nationalised industry profits is essential to the continual well being of the industries and their customers and the economy as a whole. They provide some of the funds for the very large investment programmes necessary to maintain supplies and services to the public", H.M. Treasury: "The Nationalised Industries (Cmd 7131, HMSO, London), 1978, pp.22-3.

provision of transport infrastructure involves taking account of a variety of external costs, such as environmental damage, which do not normally enter into market trading. Even for commodities which are bought and sold, the government takes cognizance of a much wider range of constraints than would be the case with private sector provision. Decisions concerning energy, for example, and the exploitation of coal, gas and oil reserves involve taking a very long-term view of the nation's needs in addition to potential short-term profits.

Although there is a single objective in the overall policy formulation, public sector undertakings require, for pragmatic reasons, to specify more concrete goals by which to guage their performance. The operational goals of different sectors vary quite substantially as emphasis is placed upon different components of the overall social welfare function. It is the differences in constraints and goals which has, until comparatively recently, prevented systematic methods of decision-making being introduced into public sector undertakings. Until the mid-1960s, decision-making in the public sector was characterised by ad hoc rules of thumb. Concern with the allocation of public expenditures in general, as expressed in the Plowden Report of 1961, led to attempts at improving decision-making throughout the public sector.

5. The problem of defining an acceptable social welfare function has exercised economists for many years, see C.D. Foster: Social welfare functions in cost benefit analysis, in J. Lawrence (ed.), Operational Research and the Social Sciences (Tavistock, London), 1966.
7. Perhaps the most tangible recognition of this need was the establishment of public expenditure review procedures in 1969. For details of the development of public expenditure management, see S. Goldman: The Developing System of Public Expenditure Management and Control (Civil Service College Studies No.2, HMSO, London), 1973.
It was realised that the traditional emphasis on inputs (i.e. the money, man-hours, etc. consumed by projects) did not sufficiently relate expenditures to the goals which were being pursued. Further, most decisions tended to be based upon short-term considerations and, specifically, on a single year's costings which seemed inappropriate for many public sector undertakings with very long-term policy horizons. Such criticisms led to the general acceptance, in broad terms, of the planning-programming-budgeting systems (PPBS) framework for decision-making. The United Kingdom was not unique in this and mirrored a trend already begun in the United States and also being pursued at a slightly slower and more measured pace in Canada, Sweden and France.

A.5.2 Planning-Programming-Budgeting Systems

One writer on PPBS once said "there seems to be an unspoken 'gentleman's agreement' that the basic terms need never be defined" and certainly discussions of the approach are beset with terminological ambiguities. Even now, no consensus on the appropriate jargon can still be taken as definite. Rather than add to the confusion by introducing new terminology or attempting to unravel the existing tangle, this paper broad accepts the definitions used by Foster.


His jargon certainly is not always consistent with other sources but it does at least provide an acceptable and uniform basis upon which to discuss PPBS. (12)

In essence PPBS is a framework within which attempts are made to identify expenditures and social outlays as closely as possible, and to relate them, in opportunity cost terms, to specific goals. Ideally, there would be one programme of action corresponding to each of the goals of the public sector. In practice, the real world involves taking into account administrative and physical considerations which prevent this ideal being attained. Government goals, for instance, usually span several of its departments which makes strategic decision-making extremely difficult. Nevertheless, the overall Public Expenditure Survey forward budget is based upon a functional classification in the PPBS manner. Despite this gradual movement, PPBS is still not employed with effect at the strategic level within the U.K. but it is widely used for tactical decision-making within departments.

(12) Strategic decisions follow from inter-departmental analysis, co-ordinated by the Public Expenditure Survey Committee, and are made collectively by Ministers early each year.) The hope is that with the aid of PPBS procedures, a department may more clearly define what its objectives are, what activities contribute to these objectives, what resources or inputs are contributing to these objectives and what is actually being achieved or what the outputs are. PPBS can be seen, therefore, as a method of organising material, marshalling facts

12. PPBS is itself often called Programme Budgeting or Output Budgeting although at other times these simply refer to stages in the wider process. Systems Analysis is another term which is often introduced and can take several meanings, sometimes with specific connotations related to operations research but frequently of a more general nature.
and ideas together, in such a way that better decisions are reached. It is not in itself a method of arriving at the 'correct' decision.

Broadly, PPBS involves the integration of three basic functions. Planning is concerned with surveying the existing situation, projecting future trends and determining appropriate goals and objectives. Programming involves formulating various projects and courses of action to achieve the agreed set of goals and objectives. Budgeting incorporates both costing (in broadest economic sense) the projects and actions to be implemented, and the establishment of a system of controls to monitor these costs. At the tactical level several forms of PPBS are employed but these can usefully be divided into two main groups which correspond roughly to the types of output of the sectors involved.

In general terms it is possible to categorise certain public-sector authorities as providing a tangible output which is, or could be, marketed: in other words, goods and services to which normal neo-classical economic demand analysis may be applied. The nationalised industries, transport, water and local authority housing are obvious examples. Such activities may be appraised using techniques akin to those employed by private-sector undertakings. The only real difference is that while private undertakings generally attempt to maximise producers' surplus (the difference between selling price and cost) public-sector undertakings in this categorisation try to maximise combined producers' plus consumers' surplus. The latter reflects the welfare enjoyed by consumers in excess of the prices they pay and may be measured by the area under the demand curve.
In contrast, there are many public sector activities for which, for one reason or another, demand is difficult to determine and, consequently, benefits are virtually impossible to assess. Such sectors often provide merit goods, where 'need' is thought a more relevant criteria than demand, and, also, frequently have complex distributional issues to consider. Health, defence, police services, and the arts, broadly fall into this category. Additional to these two main groupings, which form the focus for the remainder of the paper, there exists a pot pourri of other public expenditures which act as instruments of government policy. A whole range of activities come under this umbrella including housing grants, subsidies to nationalised industries, social security, regional location grants, etc. but they can be distinguished from the other categories by virtue of the fact that the government is not directly supplying goods or services. Public sector expenditure of this kind is only indirectly related to resource utilisation. The decision-making framework used for expenditures in this category differs from situation to situation but, because of the incidence of costs and benefits tends to be important, political considerations often dominate any economic analysis.


A5.3 The Quasi-Commercial Sector

The standard method of decision-making applied to those public sector undertakings where demand is thought the relevant criteria upon which to allocate resources is cost-benefit analysis (CBA). The underlying model is closely allied to that of perfect competition in the traditional economic abstractions of the private firm. Rather than profit maximisation as the objective, however, the aim is to select the course of action which maximises net benefits, in the very broadest sense, adjusting all costs and benefits to correspond to those that would prevail in a perfectly competitive market. The pure form of CBA was summed up over a decade ago in a well known definition found in the classic article by Prest and Turvey:

"CBA is a practical way of assessing the desirability of projects, where it is important to take a long view (in the sense of looking at repercussions in the further as well as the nearer future) and a wide view (in the sense of allowing for side effects of many kinds on many persons, industries, regions, etc.) i.e. it implies the enumeration and evaluation of all the relevant costs and benefits". The unique procedure for policy appraisal implied by Prest and Turvey has


gradually widened out, and CBA has now become rather more of a generic title for a collection of related techniques rather than the name of one specific set of calculations. In its original form, CBA superficially resembles the discounting procedures employed by large private companies and involves estimating the net present value of a project or plan by finding:

\[ \sum_{n} \sum_{i} \left( \frac{P(a_{i}, B_{i}) - P(b_{i}, C_{i})}{(1 + r)^{n}} \right) \]

where: \( P(a_{i}, B_{i}) \) represents the probable benefit expressed in monetary terms to be gained by individual (or groups of individuals) \( i \) in year \( n \) as the result of the project's completion. The benefit \( B_{i} \) is given a weight of \( a_{i} \) to reflect the importance attached to \( i \)'s welfare.

\( P(b_{i}, C_{i}) \) represents the probable cost in monetary terms to individual \( i \) in year \( n \) associated with the project. \( C_{i} \) is given a weighting of \( b_{i} \) to reflect the importance attached to the costs borne by \( i \).

\( (1+r)^{-n} \) is the relative weight attached to a cost or benefit occurring in year \( n \). The form of the weight reflects the decreasing importance attached to the more distant attributes of the project.

If the net present value is positive then the plan is accepted. When there are several options, but mutual exclusiveness limits acceptance to one, then selection is based upon the highest incremental net present value (with different sizes of alternative investments, the larger is accepted if the additional discounted benefits generated exceed the additional discounted costs). In the case of options of the same scale, the comparison of benefit-cost ratios may be
preferred on the grounds of simplicity.

In the late 1960s, this comprehensive, all-embracing CBA framework was accepted by many as the panacea to all the problems of decision-making in the public sector. It was taken up with particular enthusiasm by the transport sector where it was seen to have potential, not simply as a method of a large-scale investment appraisal (as typified by the studies of the M1 Motorway, the Victoria Line Underground Railway, the Channel Tunnel, London's system of ringway urban motorways and the siting of a Third London Airport, but also as a standard method of routine decision-making (e.g. to assess railway social service subsidies and inter-urban road investments. The 1968 Town and County Planning Act, with its emphasis on 'strategic' rather than physical planning, also encouraged the adoption of CBA for local level land-use planning decision-making. In 1967 the concept of a test discount rate (at the time 8 per cent) was introduced to encourage consistency in the temporal weighting of costs and benefits in different areas of public sector involvement and "to ensure that the calls of the public and private sectors upon resources


do not get out of line with each other over the long term". (20)

The initial enthusiasm for CBA has, however, waned in recent years and the all-embracing 'textbook' model set out above has been superseded in many areas by a variety of pragmatic adoptations. The reasons for this change of attitude are multifarious. At the most basic level there is general mistrust of any procedure which appears to offer a simple, numerical answer to difficult and delicate decisions which, by their nature, involve a variety of subjective considerations. There is a suspicion that CBA can be manipulated to provide justifications for specific lines of action corresponding to the view of the practitioner. (21) It has become apparent that there is no single, 'proper' way to perform a CBA but rather a number of alternative approaches, each corresponding to a particular set of moral notions. (22) These were problems explicitly recognised by early theoreticians in the field but their suggested qualifications and reservations were not always carried into practice. The need for decision-makers using a CBA framework to make their assumptions explicit is now widely accepted and the quasi-mechanical procedure


21. The basic underlying problem with CBA is well summed up by Wildavsky, "Although cost-benefit analysis presumably results in efficiency by adding the most to national income, it is shot through with political and social value choices and surrounded by uncertainties and difficulties of computation" (A. Wildavsky:- The political economy of efficiency: cost-benefit analysis, systems analysis and program budgeting, Public Administration Review, Vol.26, 1966, pp.292-310 (p.297)). — See also P. Self:- Econocrats and the Policy Process: the Politics and Philosophy of Cost Benefit Analysis (Macmillan, London), 1975.


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implied by the equation set down above is now treated as a starting point of a much wider evaluation of different courses of action.

More specific problems with the pure CBA model stem from putting the underlying welfare economic theory into practice. There are often considerable difficulties in physically tracing out and measuring all of the consequences of a project and, even when measurement is feasible, it is frequently almost impossible to place anything more sophisticated than arbitrary monetary values on such effects. (23) In fields where research work on evaluation has been long-standing (e.g. the valuation of time, life and noise), the techniques developed rely upon estimating the hypothetical market prices for intangibles which would prevail if they were traded in competitive conditions. Evaluations depend, therefore, on the willingness of the affected parties to pay and government dictates and priorities are considered inappropriate. (24) The partial nature of CBA makes this approach particularly unsuitable for appraising large-scale schemes or projects where wide-ranging multiplier repercussions on the economy as a whole can affect the constellation of relative prices and production which form the basis against which intangibles are evaluated.

23. An up-to-date collection of some papers setting down different approaches to the evaluation of intangibles and externalities is found in D.W. Pearce:- The Valuation of Social Cost (Allen and Unwin, London), 1978.

24. In practice, priorities and dictates do enter into the estimation procedure. An example is time evaluation; the transport ministry has, in the past, used an average value of time savings for all travellers whereas there is ample evidence that time valuation is positively correlated with the income group under consideration. The justification for the practice was to prevent undue bias being given to schemes likely to be utilised by high income groups.
The weighting schemes required in CBA procedures are particularly difficult to devise. The distributional weights reflecting the impact of a decision on different sectors of the community pose specific problems of inter-personal comparisons which must, by their nature, be subjective. In addition, although the test discount rate (and, more recently the recommended rate of return) represents an attempt at introducing standard temporal weights across areas of public sector activity, the rates used are somewhat arbitrary and only partially reflect the social opportunity cost of resources. The actual estimation of the time stream of costs and benefits is itself difficult and the introduction of sensitivity and other, usually cruder, techniques to reflect the stochastic nature of the forecasts introduces further elements of subjectivity.

This lengthy list of criticisms levelled against the pure CBA approach, and the obvious defects of the technique as a practical tool for assisting in public sector decision-making in all but special cases, has led to a number of variants of the basic model being

25. Early CBA studies excluded such weights, being simply interested in aggregate costs and benefits. They were founded on the so-called Kaldor compensation principle (N. Kaldor:- Welfare propositions and interpersonal comparisons of utility, Economic Journal, Vol.49, 1939, pp.549-52). This essentially says that if the strict Pareto criteria cannot be met (i.e. it is impossible to benefit one person without making another worse off) then a weaker practical test is to see whether it would be possible for the losers to compensate the gainers. No actual compensation need take place, however: compensation just has to be potential. The work of Little (I.M.D. Little:- A Critique of Welfare Economics (Oxford University Press), 1950) in the 1950s has slowly permeated CBA practice and with it questions of equality have supplemented those of efficiency. Little advocates the need to both meet a Kaldor type test and provide evidence that the project improves income distribution.

developed. The nature of these modifications depend, in the main, on the relative importance attached to the various constraints confronting the decision-makers in the individual sectors, and upon the types of goals envisaged as appropriate for the kind of activity being considered. In transport, for example, the problem of placing acceptable values on all intangible costs of road investments has resulted in the employment of a two-stage procedure. COBA, a computerised package, evaluates those effects which are comparatively easy to quantify and forecast, and where evaluation methods are relatively well advanced (i.e. changes in vehicle operating costs, journey travel times and accident rates). Such results, appropriately discounted, are then subjected to discussion at public enquiry. It is here that wider social, environmental and distributional questions can be raised. The difficulty of comparability between the quasi-scientific evidence offered by COBA and the unquantified, verbal account of the wider social issues of a road investment, however, causes serious disquiet. A similar problem arises when it is impossible to assess the longer-term effects of a course of action; again, comprehensiveness must be sacrificed. In the case of the London urban motorway proposals, for example, the sheer complexity of tracing out the temporal pattern of interacting transport demands over a complicated road system resulted in the calculation of only a first year rate of return.

In other areas, the problems of evaluatory intangibles costs or forecasting the long-term implications of a project are not the main causes for concern. Rather, there are difficulties in assessing the monetary value of benefits; a situation not unusual in public sector
undertakings whose actions have wide-ranging impacts throughout the economy. Under such circumstances, it is often common to view the decision-making process in terms of cost-effectiveness. (27) Klarman et al. (28) provide a useful definition, "Cost-effectiveness, rather than cost-benefit, is employed when various benefits are difficult to measure or when the several benefits that are measured cannot be rendered commensurate. Under cost-effectiveness analysis costs are calculated and compared for alternative ways of achieving a specific set of results". In such cases, it must be possible to set goals in physical terms so that the exercise becomes one of selecting that course of action offering the lowest opportunity cost method of meeting these goals. Hence, projects are assessed in terms of cost per unit of output.

The Central Electricity Generating Board (CEGB) uses a cost-effectiveness approach when deciding upon investment policies with regard to new generating capacity. The future demand for electricity is determined and the plant accepted which offers the greatest discounted cost saving over the expense of making more use of the oldest existing capacity. Where a single goal of this kind can be specified, the technique has practical qualities, but in most cases there are

27. There is some problem with terminology here but cost-effectiveness may be likened to cost-minimisation in the private sector where some predetermined output level has been decided upon independently. Trade-off analysis involves more abstract goals than cost-effectiveness (e.g. in the case of transport it may be time savings or reduced accidents, while cost-effectiveness concentrates upon physical goals such as four-lane motorway mileage) and is a more refined, though not necessarily practical, variant of it.

secondary goals (e.g. in the case of CEGB, safety is clearly important) which cannot easily be ignored. In these cases, there are serious trade-off problems in selecting priorities amongst the goals. Further, the ideal cost-effectiveness study employs measures of opportunity cost which often present difficulties as severe as those encountered when trying to quantify and evaluate benefits. For these reasons, cost-effectiveness analysis is most helpful in deciding upon the most efficient way of implementing a prior made decision. In the case of the CEGB, for instance, it is stated policy to have sufficient capacity to meet demand and with the location of a Third London Airport (which was strictly a cost-effectiveness study)\(^{29}\) it had already been decided a new airport was required and only the question of the siting was at issue.

A5.4 The Social Sector

The 'merit' nature of services provided by health, defence and education authorities, combined with the distributional and public goods (i.e. goods where the exclusion principle cannot apply) problems associated with these sectors, precludes the practical application of CBA techniques. In particular, the idea of evaluating intangibles in terms of ability to pay is felt to be especially inappropriate. In their place output budgeting is employed with goal orientated accounts as the primary basis for analysis. The technique was initially adopted by the Ministry of Defence for the Defence Policy Reviews in 1964 as 'functional costing' and soon taken up by the Department of

\(^{29}\) Commission on the Third London Airport, \textit{op. cit.}\)
Education and Science (30) and the Home Office, concerning police in particular, (31) with the Department of Health and Social Security (32) following in 1971. The technique essentially concerns devising the allocation of resources within a sector in such a way that changes in this allocation reduce society's wellbeing. The allocation is, therefore, within the sector, a Pareto optimal one.

It has been pointed out by Byatt (33) that this necessarily assumes both that the sector in question is fairly clearly delineated, with resource consumption well represented by public outlays in the sector, and that output categories may be clearly and discretely defined without problems of cost allocation. While the first condition is quite well satisfied by most of the government sectors employing the technique, output categorisation does pose problems with respect to the second criteria.

Some sectors suffer from the problem of relating outputs to goals; outputs often overlap several goals and vice versa. In defence, for instance, the programme budget is presented in terms of output expenditures, rather than commitments or goals, because of,


firstly, the multi-purpose nature of the forces retained and, secondly, the complex relationship between general support and front-line activities. Education is an area where it is easier to relate outlays to specific groups (i.e. nursery education, higher education, education for the 16-19 year olds, post-graduate education, etc.), but, again, it is impossible to relate these outlays to the underlying goals of education (e.g. social cohesion, higher labour productivity, etc.). The degree of interdependence between different outputs and different goals, the problem of separating means from ends, makes it impossible in practice to allocate costs in the required fashion.

While the programme budget approach permits an assessment of the relative costs of switching resources between different activities and outputs, specific issues arising within defence, education and the like are often subjected to more detailed 'special studies'. Special studies form an important part of the programme budgeting approach of these sectors and usually involve the application of either CBA or cost-effectiveness procedures. The complexity of attempting to utilise these techniques in the educational, defence and health fields increases the resource costs of decision-making substantially and, in general, this type of treatment is either reserved for topics where difficulties of quantification are less severe or where the need to make the appropriate decision is central to the overall success of the department's policy. In the case of health, for example, cost-effectiveness techniques have been applied to assessing the desirability of alternative treatment mixes.
offering identical results, similarly there have been CBA studies of educational projects. Basically, these special studies are employed in order to select from a set of alternative actions each leading to a previously specified goal.

A5.5 Multi-Criteria Approaches

The multi-facet nature of the social welfare function which public sector undertakings are concerned with maximising, together with the constraints confronting management in these sectors, underlie the problems of decision-making. With those sectors taking demand as the parameter for benefit measurement, CBA techniques provide only a partial solution to the problem, while the socially orientated sectors have difficulties in weighting their numerous goals. In the face of these difficulties the need for new approaches to decision-making is becoming widely accepted. The Chairman of British Rail points, for example, to the need for an approach which "can be understood by ordinary intelligent people ... incorporates the methods of analysis developed by welfare economists over the last decade or so, ... gets away from the naive position adopted by early cost benefit man which seemed to imply that every consideration could be perfectly weighted and that


therefore there was a single best solution". (37) The Leitch Report on trunk road investment takes a similar stance, "the right approach is through a comprehensive framework which embraces all the factors and groups of people involved in scheme assessment. (38) There is also some discussion over the need for such changes at the local authority decision-making level. (39)

Multi-criteria decision-making techniques move away from the idea of maximising and are more akin to the management theories of satisficing. (40) Rather than attempting to seek optimum solutions, which, for practical reasons, are likely to be unobtainable, the decision-maker selects actions complying with a range of criteria which describe minimally satisfactory alternatives. In the case of education, for example, one seeks options which provide certain set levels of literacy, numeracy, etc. rather than alternatives which maximise goals, say literacy, at the expense of others.

37. The railways encounter particular difficulties in making investment decisions. Part of British Rail's operations (e.g. inter- city and freight services) are committed to straightforward commercial criteria while other services are deemed socially necessary and are assessed using CBA type techniques. Allocation of resources between these two types of activities poses serious problems because of the incompatibility, except in highly stylised circumstances, of the different types of return calculated, see A.J. Harrison and P.J. Mackie: The Comparability of Cost Benefit and Financial Rates of Return (Government Economic Service Occasional Paper No.5, HMSO, London), 1973.


Decision-making models based upon this type of framework are still in their infancy, certainly as far as practical applications are concerned. Land-use planning and regional policy analysis are exceptions to this situation and a variety of multi-criteria techniques have been developed and tested in these areas. It seems probable that some of these methods may have potential for wider application in other areas of public sector involvement.

The planning balance sheet (PBS), initially developed by Lichfield for town planning purposes, is similar to CBA in that all costs and benefits are included and that distributional considerations are not neglected, but it is a movement in the direction of multi-criteria analysis in that not all the effects of the various schemes are translated into monetary terms. Where evaluation is difficult, physical values are used, and when quantification is impossible, ordinal indices or scales may be employed. A socio-economic account is drawn up setting out the full effects of each course of action indicating the extent to which various groups in the community will be affected. These are then compared to the predeter-


mined planning goals which are selected as reflective of community needs. Alternative plans are ranked under each objective heading using ordinal ranking procedures and the ranks are then added together to produce a ranking of the plans with respect to the objectives taken as a whole - the scheme with the lowest algebraic total being deemed the best. A modified version of this type of approach, the project impact matrix, has recently gained the favour of the Leitch Committee. (43)

The PBS attempt to extend CBA into a multi-dimension framework, however, requires substantial data inputs and only offers a partial solution to the problem of making inter-personal comparisons. (44) The ranking-process has to reflect social preferences which are themselves difficult to ascertain and, even if a consensus is possible, the ordinal nature of the ranking suggests a loss of efficiency in the technique. Although value judgements cannot be avoided, the PBS approach has the merit that, unlike the pure CBA model, these are made explicit rather than hidden in a final single NPV figure. The construction of the initial socio-economic account can often, in itself, be educational and shed considerable light on salient questions the decision-maker should be asking.

The PBS method falls between CBA and multi-criteria decision-making methods, containing elements of both the maximisation principles underlying CBA but without the emphasis on monetary evaluation of all the projects' effects. Multi-criteria decision-

43. Department of Transport, op. cit.

making techniques generally involve introducing weights to reflect the relative priorities attached to the various outcomes associated with different courses of action. Although these weights may be ordinal in nature, they are more often cardinal, being based upon available empirical evidence. A number of multi-criteria approaches have been devised each attempting to achieve a multi-dimensional compromise between the wide diversity of goals and costs which are embodied in public sector choice. The approaches differ in their method of presentation, the level of mathematical sophistication involved and the amount of data input required. Several of the techniques rely upon geometrical representation to produce multi-dimensional scalings,\(^{(45)}\) while others involve a considerable degree of intuition. In general, however, these particular techniques tend to be rather specialised in nature and are only of practical use in certain, specific and unusual circumstances. Of more practical value are some of the weighting techniques which already enjoy a degree of practical acceptance and for which the theory is comparatively well advanced.

The introduction of weightings permits the effects of a projected action to be reduced to a single, summary figure offering the possibility of direct comparisons with other options. Variations on this theme abound.\(^{(46)}\) The goal-achievements matrix approach,\(^{(47)}\) for


46. See, P. Nijkamp and A. van Delft, op. cit., for a wide-ranging survey of the various multi-criteria techniques which have been developed although few have to date been employed in actual decision-making exercises.

example, offers an explicit treatment of various goals and applies a set of predetermined weights to them so that each option can be assessed in terms of goal achievement. To facilitate this, the goals are related to physical measures to reflect the extent to which they have been achieved. The final goal-achievement account employs the weighted index of goal achievement to determine the preferred course of action. Another variant, concordance analysis, offers pair-wise comparisons of alternatives by estimating two indices: the first, the concordance index, reflecting the weighted degree by which one project dominates the other in terms of the goals met and the second, the disconcordance index, showing the weighted degree to which it is itself dominated.

To date, much of the work in the field of multi-criteria decision-making has focused on devising mathematically consistent methods of handling weights and basic data. The major practical problem, however, is in devising the weighting scheme to adopt; CBA may be seen as a special case of the multi-criteria approach in this context, with monetary values being employed as weights. Despite the practical difficulties of evaluating intangibles and the problems of equality, the CBA method is possibly more readily accepted than some of the alternative schemes suggested for multi-criteria procedures. The idea of adopting the implicit weighting scheme of past decisions, for instance, has the desirable merit of assisting in the continuity of decision-making but, even if a practical method of excavating such weights from the past was devised, the implicit assumption that the motivation behind past decisions were correct and socially desirable is open to question. Further, past decisions were based upon social
proprieties and morals of the period in which they were made and these are unlikely to have held constant. Indeed, since public sector decisions have very long-term implications, past actions are even less likely to reflect the priorities of future generations. Suggestions that the weights could be derived from political debate, say, in the House of Commons, begs the question of quantification and assumes full information on the part of speakers. A further proposal that hypothetical questioning of individuals about imaginary decisions will reveal preferences (48) has an academic appeal, but the problem of ensuring unbiased responses, and the doubtful general applicability of the answers obtained, suggests severe practical limitations.

A5.6 Conclusions

The very nature of the goods and services provided by the public sector renders the profit maximising models widely employed to describe private sector decision-making inapplicable. This is not to say that in certain areas of public sector activity there is not an objective function similar to that generally associated with the private sector but rather that the perception of the public sector is much wider. The models underlying CBA and cost-effectiveness analysis have their counterparts in the standard economic theories of profit maximising and cost minimising but the costs and the benefits considered are much more diffuse and the view taken, much longer. Recent developments at the theoretical level, together with

the views of some management and advisory bodies, suggest that there are movements in the public sector to shift away from the traditional maximising/minimising approaches to decision-making and towards the acceptance of a set of much weaker, but more pragmatic, approaches. In particular, the interest shown by British Rail, local authorities and road investment agencies in multi-criteria assessment techniques indicates that notions of satisficing are replacing those of maximising. It seems very doubtful, however, whether with our current state of knowledge, multi-criteria assessment can, in the short term, do more than make some of the assumptions underlying existing methods more transparent. The emphasis on specifying the exact objectives being pursued and the setting out of the repercussions of decisions may, however, in the longer term induce a greater public involvement in public sector decision-making and, with this, the necessary information of society's preference function may be revealed. Certainly, the complexity of many existing public sector decision-making aids tends to discourage social involvement.
APPENDIX 6

BIBLIOGRAPHY OF REFERENCES CONCERNED WITH CAR OWNERSHIP MODELLING AND FORECASTING

This list offers over 200 references relating to car ownership modelling and forecasting. It represents a considerable up-dating, expansion and revision of the list found in A.S. Fowkes, K.J. Button and A.D. Pearman: Car ownership modelling and forecasting - an annotated bibliography, Institute for Transport Studies, Working Paper 121, University of Leeds, 1979. The original source, in addition to providing a somewhat shorter bibliography, does offer a full annotation and 'coding' of the various items listed.


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