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I certify that this thesis is my own work.

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DEDICATION

I dedicate this thesis to my parents, John and Mary Dunne, without whose support this work would not have been possible.

MODE CHOICE IN NEW TOWNS: A CASE STUDY OF LIVINGSTON

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CHAPTER 1

INTRODUCTION

1.0 OBJECTIVES

The major objective of this study is to contribute to the understanding of the most important aspect of travel demand, namely mode choice for the journey to work, within the context of the "New Town" form of urban development. To this end the study employs recently developed disaggregate probabilistics models of consumer choice. The approach recognises the inherent probabilistic nature of transport choices, operates at the level of the individual decision unit and explicitly considers the quantal nature of transport mode choice. These models can be applied to to data obtained from Livingston New Town's Travel and Employment Survey in 1975. In this way the study provides useful information on the determinants of mode choice within Livingston New Town, with implications for other New Towns, and the possible development of transport structures within the more traditional forms of urban development.

To the author's knowledge this is the only study to apply disaggregate probabilistic models to a New Town and so provides both a novel approach to the analysis of travel demand in New Towns as well as a novel application of the models used. The distinctive features of the application relates to both the form of the journeys considered; the journey to work between a New Town and it's nearest conurbation and the consideration of walking as a feasible alternative to car and public transport for the journey to work within the New Town. Further, the study illustrates that disaggregate models can provide useful analysis when calibrated on ordinary travel survey information, together with engineered level of service variables. This has clear implications for the practicability of such models in transport planning.

In addition the study investigates the use of disaggregate probabilistic models for prediction, both in terms of providing aggregate models of travel shares and and of estimating the effect of changes in policy controllable variables. In

this way important information on the application of these relatively neglected procedures is provided, together with a detailed assessment of available elasticity measures. Within the analysis of the elasticity measures, some novel considerations of the forms of elasticities are made, in categorising both arc and point elasticities and a practically appealing approximate elasticity measure.

1.1 OUTLINE

Before embarking upon the specific analysis of mode choice in Livingston New Town, it is clearly necessary to consider the form of development provided by the "New Town" label and to consider the characteristics of Livingston within this context. This task is undertaken in the first two chapters. New Towns are shown to differ markedly between themselves as well as in comparison to typical urban developments. In this analysis, Livingston presents itself as a most useful object of study. It is seen to reflect many of the distinctive features of New Town developments in an extreme form, in terms of it's physical and socioeconomic characteristics. Further, the town, with it's extreme commuting levels, transport orientated development and high car ownership, might be considered to typify half the fundamental transport planning choice facing towns and cities. Describing how they would appear if emphasis was put of the use of cars and walking to complement public transport. This clearly gives the result of the study wider implications than simply understanding the determinants of mode choice within Livingston.

The next stage in the study is the presentation of the disaggregate probabilistic models of consumer choice to be employed in the empirical analysis. This is undertaken in Chapter 4. Disaggregate behavioural models, although only recently developed, are by now a useful established method of analysis, thus the arguments for using such models are considered only briefly. The form of the models and their derivation from probabilistic choice theory are then presented and the structure of travel and related choices examined. Finally, the problem of estimating the non linear in parameters models is considered and the maximum likelihood estimation approach to be used in the study is presented.

Having provided the context and method of analysis the next part of the study is concerned with the empirical analysis of the journey to work between Edinburgh and Livingston. Chapter 5 investigates the forms level of service variables available to the study, outlining the practical limitations of the data, the creation and justification of engineered values and the empirical derivation and selection of the best variable forms. Secondly Chapter 6 investigates the validity of other available explanatory variables, both proxies for excess travel time and socioeconomic variables, at both the individual and household levels. The approach taken to deal with the problems of car availability and the resulting sample separation are then outlined. Lastly, the final model forms, based upon the selected explanatory variables for the sample separation employed are presented.

Building upon the extensive analysis of Chapter 5 and 6, Chapter 7 presents the analysis of the journey to work within Livingston. The available socioeconomic and level of service variables are analysed and the final model forms presented. The results obtained are then compared with the previous analysis of the journey to work between Livingston and Edinburgh.

The next two chapters concern the use of disaggregate probabilistic models for prediction. Chapter 8 considers the aggragation problem. Considering the justifications for aggregating from models estimated at the individual level rather than using an aggregate model directly and then presenting the available approaches; naive, enumeration, statistical differentials, density function and classification. These are then applied to the journey to work between Edinburgh and Livingston and a comparative assessment is made. Chapter 9 then deals with the prediction of the effect of changes in characteristics on mode shares. The various elasticity measures micro and aggregate, point and arc are analysed together with their continuous analogues based upon the density function approach to aggregation. These are then applied to the Edinburgh - Livingston study and comparatively assessed with emphasis on their inherent biases. Finally the use of the density function approach to provide simulation of other effects of policy controllable variable changes is considered empirically.

The final chapter draws some implications and conclusions from the study both as regards the nature of travel demand in the new town and the use of disaggregate probabilistic models in such application.

CHAPTER 2

NEW TOWNS

2.0 INTRODUCTION

As a prerequisite to the analysis of mode choice in Livingston New Town this chapter attempts to provide some definition of the actual form of development implied by the New Town label. The first section outlines the genesis of the New Town idea and its historical development. The next two sections then consider how New Town developments might be defined, in terms of how they differ from orthodox urban developments, both in planning aspirations and physical and socioeconomic structure. This attempt at definition being complicated by the divergences between the New Towns themselves.

2.1 BIRTH OF THE NEW TOWN IDEA

Throughout history there have been thinkers who have condemned existing social conditions, in many cases seeing the creation of "perfect" cities as a solution to their grievances. Such Utopian idealism, was however, far from the idea of the New Towns as we know them today. Rather the genesis of the New Town idea in its more practical, though still idealistic form is to be found in the advent of the industrial revolution.

The industrial revolution was typified by rapid industrialisation and urbanisation. The development of capitalism with its new methods of production destroyed much of rural industries and together with the enclosures drove more than half of the population to the towns. This caused cities to grow at rates comparable to the twentieth century, but with appalling conditions of growth. Overcrowding, poverty, crime, disease and unsanitary conditions typified these urban developments, while the wealthy moved to the new fashionable suburbs which began to encroach rapidly on the surrounding countryside.

Many reformers saw "new settlements" as the solution to urbanisation. Robert Owen created his "ideal village" in New Lanark to provide his workers with a more civilised life style and towards the end of the nineteenth century other philanthropic factory owners created model villages to accomodate their workers. Thus, Salts' "Saltaire" was constructed to the north of Bradford, Lever's "Port Sunlight" just outside Liverpool and Cadbury's "Bournville Village" in Birmingham. Though these developments represented an important step forward ideologically and were not confined in influence merely to Britain, few factory owners were willing to risk loss of profit for an increase in the welfare of their workers. As a result, these Utopian experiments, lacking as they did any diversified industrial base to act as a buffer against trade fluctuations did not have a lasting effect on urban development.

Instead, the concept of New Town development took form in the writings of Ebenezer Howard, "Tomorrow a Peaceful Path of Real Reform" published in 1898 and "Garden Cities of Tomorrow" published in 1902. Howard's ideas were somewhat simplistic, from the modern point of view, with the proposed merger of town and country elements in urban development being attained by clusters of interdependent satellite towns, connected by rapid transportation, plenty of open space and a diversified economic and agricultural base. The problem of high urban rents was to be overcome not by nationalisation, as was being proposed, but by municipalisation of rural land bought at agricultural prices and converted to urban use, with dwellings rented by the occupiers.

Howard earned the title of "Father of the New Towns" by doing more than putting forward his ideas, rather he attempted to put them into practice. In 1901, he created the Garden City Association (now called the Town and Country Planning Association) a voluntary association which has proved an active and influential protagonist of metropolitan decentralisation. Then, in 1903, the First Garden City Company was formed to develop a new town at Letchworth, Hertfordshire, 34 miles from central London. Public support for this venture was forthcoming, though not in the necessary financial form, thus many cherished principles had to be foregone. The project did, however, slowly go ahead and provided useful practical experience of such forms of development, though it was many years before shareholders received dividends on their capital.

In the aftermath of the First World War, Howard and his supporters attempted to influence the government's building program by presenting satellite towns as an alternative to the spread of semi-detached suburbia, but met with little success. Then, in 1920, a second Garden City was launched at Welwyn in Hertforshire with requests for "non-profiteering investment" from the public. Despite financial problems in the early stages, the development went ahead and the town developed successfully, with the government finally stepping in with loans and then taking over construction as part of the London overspill program.

This action represented the beginning of the acceptance of the necessity for central planning control on urban development.

The devastation in the aftermath of the Second World War finally brought the need for positive action, along the "satellite town" lines, and centralisation of planning, to curb the spread of suburbia. Though government committees had earlier reacted favourably to the New Town developments it was not until the Reith Committee's analysis of the promotion of such developments, and the resulting 1946 "New Town Act" that the Government took direct action and the New Town movement achieved official acceptance and positive effect.

2.2 GENERAL AIMS OF NEW TOWNS

Although New Towns possess a separate administrative identity from other urban developments, they cannot be considered as a homogeneous group, nor can a sharp distinction be drawn between them and other forms of urban growth. There are, however, a number of factors which could be considered to represent the archetypal New Town and which existing New Towns possess, or are intended to possess, in varying degrees. New Towns should be comprehensively planned by a development corporation, with a large proportion of the property owned by this non-profit making public body. They generally exhibit rapid population growth from a relatively small base and are spatially separate from a parent city and hence, built on land acquired at a lower cost than at the periphery of conurbation. When the New Town reaches its target size the development corporation hands over the assets to the New Town Commission.

In attempting to classify New Towns, some of the greatest deviations lie in the degree of achievement of the aims proposed by the Reith Committee that New Towns should be "self contained and balanced communities for working and living". These interrelated goals of "social balance" and "self containment" represented rather vague directives as to the required form of development. Thus, they have incited differing implications for the forms of development, as circumstances have changed over time.

Social balance had as one of its main implications, the accomodation of low income groups within the New Towns. This was mainly to abate the fear that New Town developments would take the form of the one class community dormitory suburbs typifying the suburban sprawl. The assessment of social balance has generally been made with reference to national averages, though some other terms of reference, such as similar sized towns might be more appropriate. Further, although it is possible to consider employment characteristics as a measure of social balance, the large proportion of manufacturing industry in the New Towns will clearly have a significant effect upon the employment structure. It should be noted that the aim of social balance is not merely ideological, but also, practical as without an adequate social mix including the upper social groups, New Towns would find it difficult to attract social and cultural amenities.

Self-containment relates to a number of factors within the New Towns. They were clearly designed to be centralised forms of urban development and as such their spati al concentration required that the provision of facilities, in terms of employment and amenities, be adequate to prevent the necessity of travel from the town. Clearly this aim is related to social balance as it would not really be possible to have self containment without social balance.

In attempting to achieve balanced communities, the New Towns originally concerned themselves with matching population and employment, both in number and type, and providing adequate amenities (although this was difficult as it was hard to get shops, etc...to move on the basis of potential, rather than actual, demand). When this was combined with the allocation of housing to those with jobs in the town, a high degree of self-containment was achieved. The increases in personal mobility and car ownership over time, however, caused a change in the role of the New Towns to that of providing regional growth centres and in many cases to the phasing out of the jobs/house package. These developments made the goal of self-containment, at least as regards work journeys, less important. In many cases, the use of New Towns as regional growth centres and hence their

important role within the region caused large flows in and out of the community and led the Development Corporations to aim for balanced commuting rather than self-containment.

Besides these broad social and economic goals, one aim of the New Towns has always been environmental improvement to gain the advantages of both town and countryside. The early New Towns provided extensive open spaces and gardens with low density housing[1].

The increase in car ownership and personal mobility, however, led to more ambitious transport policies and the later developments were planned to aid these, although the features of open spaces and segregated footpath systems were still retained.

Having considered the general aims of the New Towns it is now worthwhile to analyse in more detail, the types of New Towns and how they differ from each other.

2.3 TYPES OF NEW TOWNS

Following the Reith Committee's recommendations, the post World War Two Labour Government designated 14 New Towns including 8 around London and 2 in Scotland. The London New Towns and East Kirkbride in Scotland were part of overspill programs but the others were for the far more localised purposes of relieving unemployment or providing housing in areas of economic growth. The program halted, in the 1950's, with a change in political attitudes to

1. **There has been an increase in housing density but less concern about it because of the increased mobility.**

development, with only Cumbernauld being designated in 1955. The Conservative Government's threat to abandon the program was, however, never realised and by the end of the decade a second phase of New Town development was underway, carrying into the 1960's with the Labour Government continuing with policies already in the pipeline.

The second wave of development in the 60's, which included Livingston, contained radical changes in both planning philosophy and objectives. The New Towns were planned on a much larger self-contained scale and in many cases developed on the base of a large initial population with the aim of providing regional growth centres in depressed areas. These attempts to create what might be termed "new cities" certainly reflected the success of previous developments in stimulating economic growth. In the changed conditions of the 1970's, however, the scale of such plans was seen to be over ambitious and myopic and were modified to abate such criticism, Inner City development becoming increasingly more important.

Given these developments and the changes in ideals and objectives over time, it is not surprising that the most common classification of the New Towns is that based upon the date of designation. In this way, it is possible to distinguish "Mark I" New Towns, relating to the lst phase of development, which reflect the Garden City ideals of Howard, with low density housing in distinct neighbourhoods (with a local shopping centre and primary school), but with lots of open space especially around the town centre. These New Towns were generally developed on greenfield sites with industry concentrated on a few sites and segregated from dwellings. The road system tended to be curvilinear in shape and not designed to act as major arteries. There were, of course, divergences in the form of development between the towns, mainly related to whether or not there was rapid build up during the initial stages.

The "Mark II" New Towns, or second wave of development, came several years later and reflect the impact of increasing car ownership on personal mobility and hence, the necessity to incorporate an efficient transportation framework in planning. Thus, these towns tend

to have compact linear shapes and higher density housing, with much more emphasis given to the transport system. There was, however, a considerable degree of individuality in the provision of facilities for public and private transport, often influenced by the large pre-designation base of some of the towns.

A further distinction can be made by considering "Mark III" New Towns as those with large existing pre-designation urban structures, mainly developed around existing town centres. The difference in age between Mark II and Mark III New Towns, however, is not great and hence they are generally lumped together.

Champion, Clegg and Davies (1977) regard these groupings as deficient in their being concerned with physical criteria and not considering population characteristics. Attempting to improve upon this they consider rates of population growth of the New Towns together with their age and consider a five-fold classification.

Group 1 - Crawley, Hatfield, Hemel Hempstead and Welwyn Garden City
- designated by 1950 with rapid intakes of population mostly completed by 1960 and transferred to the New Town Commission.

Group 2 - Aycliffe, Basildon, Bracknell, Corby, Cwmbran, East Kilbride, Glenrothes, Harlow, Peterlee, Stevenage
- also designated by 1950, but their fast population growth continued into the sixties and in some cases into the seventies. (Mainly as a result of expansion of targets or lagged earlier development).

Group 3 - Cumbernauld, Livingston and Skelmersdale
- designated between 1955 and 1962 with relatively small initial populations and a rapid build-up after 1961 which slowed in the 70's.

Group 4 - Irvine, Milton Keynes, Redditch, Telford and Washington

- designated between 1963 and early 1967 based on substantial existing settlements with rapid growth in the seventies.

Group 5 - CLNT, Newton, Northampton, Peterborough and Warrington

- designated since early 1967 with large initial populations relative to their targets and mixed records of growth.

These classifications were further tested by applying factor and cluster analyses to hypothesised distinctive New Town features namely, variables reflecting recent growth trends ("newness"), social characteristics, regional influences, self-containment and the degree of satisfaction of residents to the New Town environment. Champion et al proxied these factors by various variables available from census data and found evidence to support the five-fold grouping.

It would appear that although the common classification of the New Towns does have some relevance, it can be improved upon and will be of limited use in studying any individual New Town. Thus, to analyse the form of development of Livingston, it is necessary to give consideration to a more detailed analysis.

CHAPTER 3

LIVINGSTON NEW TOWN

3.0 INTRODUCTION

The attempt to provide some definition of a New Town, although identifying some common features, has shown that significant divergence can exist between the New Towns themselves. As a result the importance of a more detailed and specific analysis of Livingston was recognised. This chapter provides such an analysis of the form of development of Livingston New Town relative to more usual urban developments and other New Towns. The first section provides an introduction to the New Town and gives its geographical location; the second section outlines its physical structure; the third section analyses its socioeconomic characteristics. Finally these features are summarised and the implications of the analysis for this study are concluded.

3.1 BACKGROUND AND LOCATION

Livingston is located in the Lothian region of the central industrial beltof Scotland some 15 miles from Edinburgh and some thirty miles from Glasgow. It is central to the Scottish motorway system (see Fig. 3.1 and Fig. 3.2) and has direct access to the east and west on the M8, to the north on the M9 and M90, and to the rest of the UK on the M75 (A74). This locational advantage, within 43 miles range of four Universities, two international airports and two major ports, has been a key factor in the town's attractiveness to a wide range of industrial and commercial development. Transportation, especially road, has been an important growth factor, with the locational advantages being realised through improvements in the transportation network.

The town was designated in April 1962 and was Scotlands fourth New Town following East Kilbride, Cumbernauld, and Glenrothes. Originally its main aim was to provide employment and housing for families

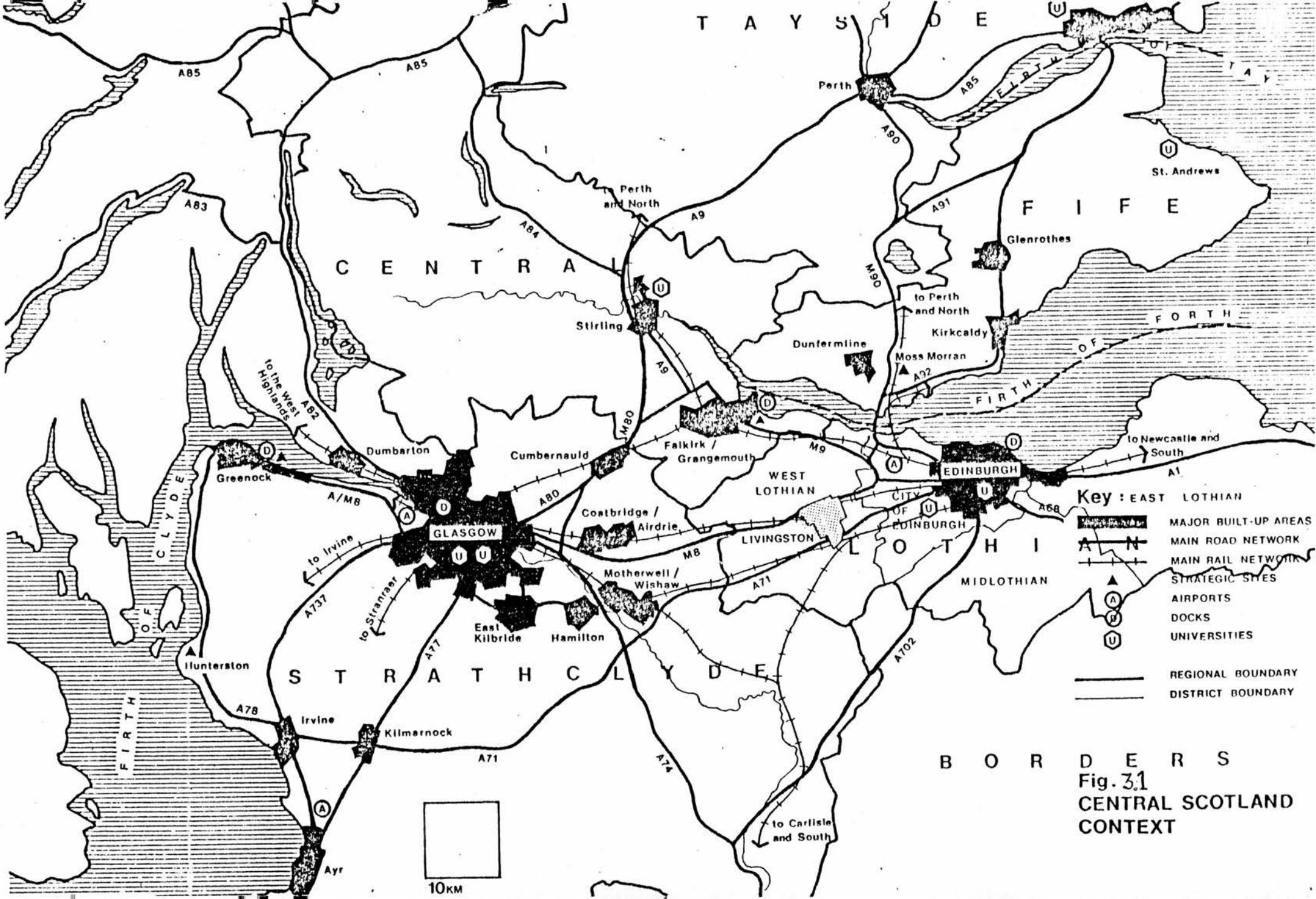


Fig. 3.1
CENTRAL SCOTLAND CONTEXT

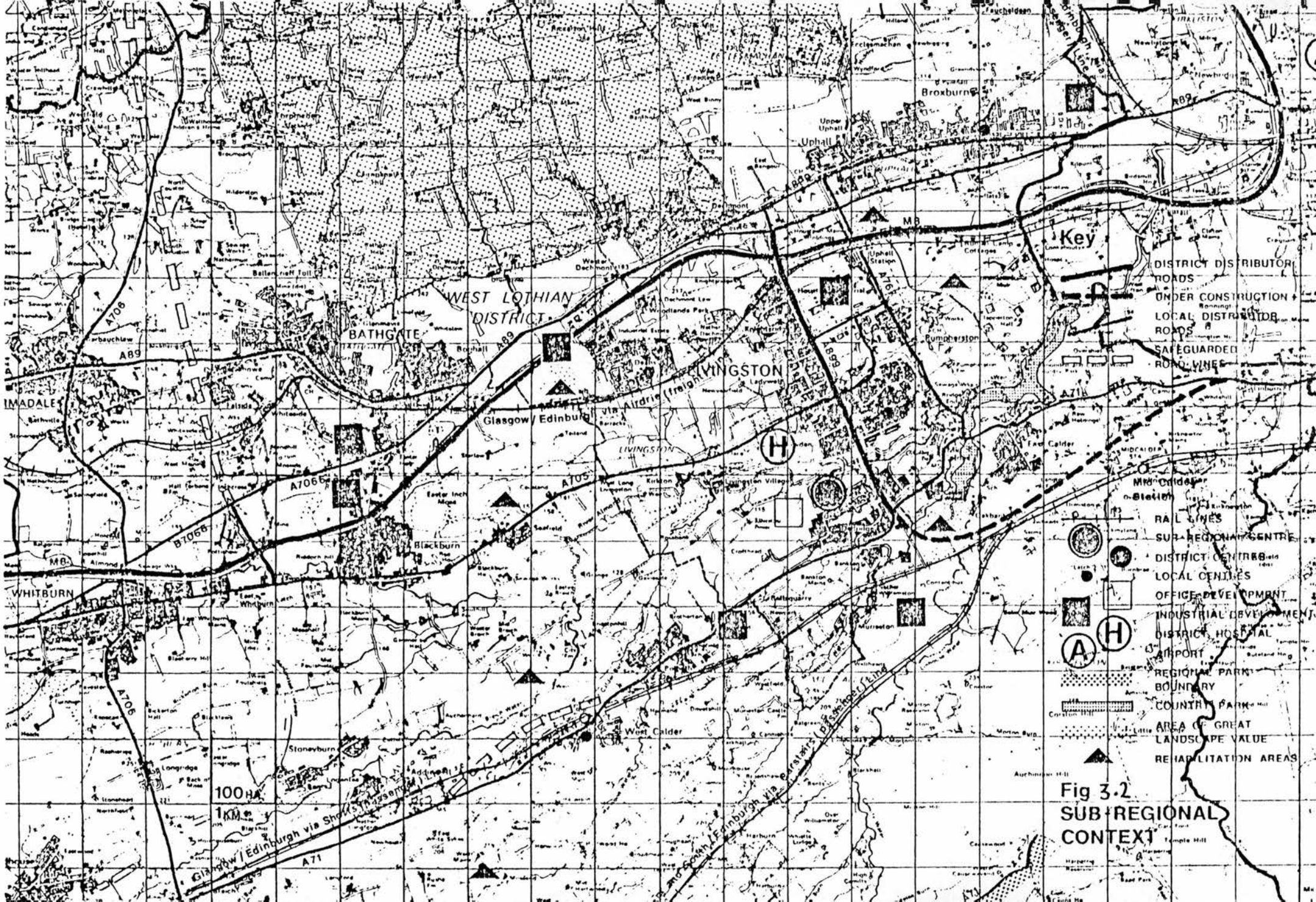


Fig 3.2
SUB-REGIONAL CONTEXT

displaced by the redevelopment of Glasgow, as the existing provisions (within Glasgow and the existing New Towns) were reaching capacity. There was, however, the additional aim of providing a focus for investment and growth within the sub-region which had long been dependent on coal mining and oil shale extraction and had become a largely neglected area as these activities had declined. Thus the New Town was to provide a condusive environment for industrial development and so rejuvenate the the regional and Scottish economy.

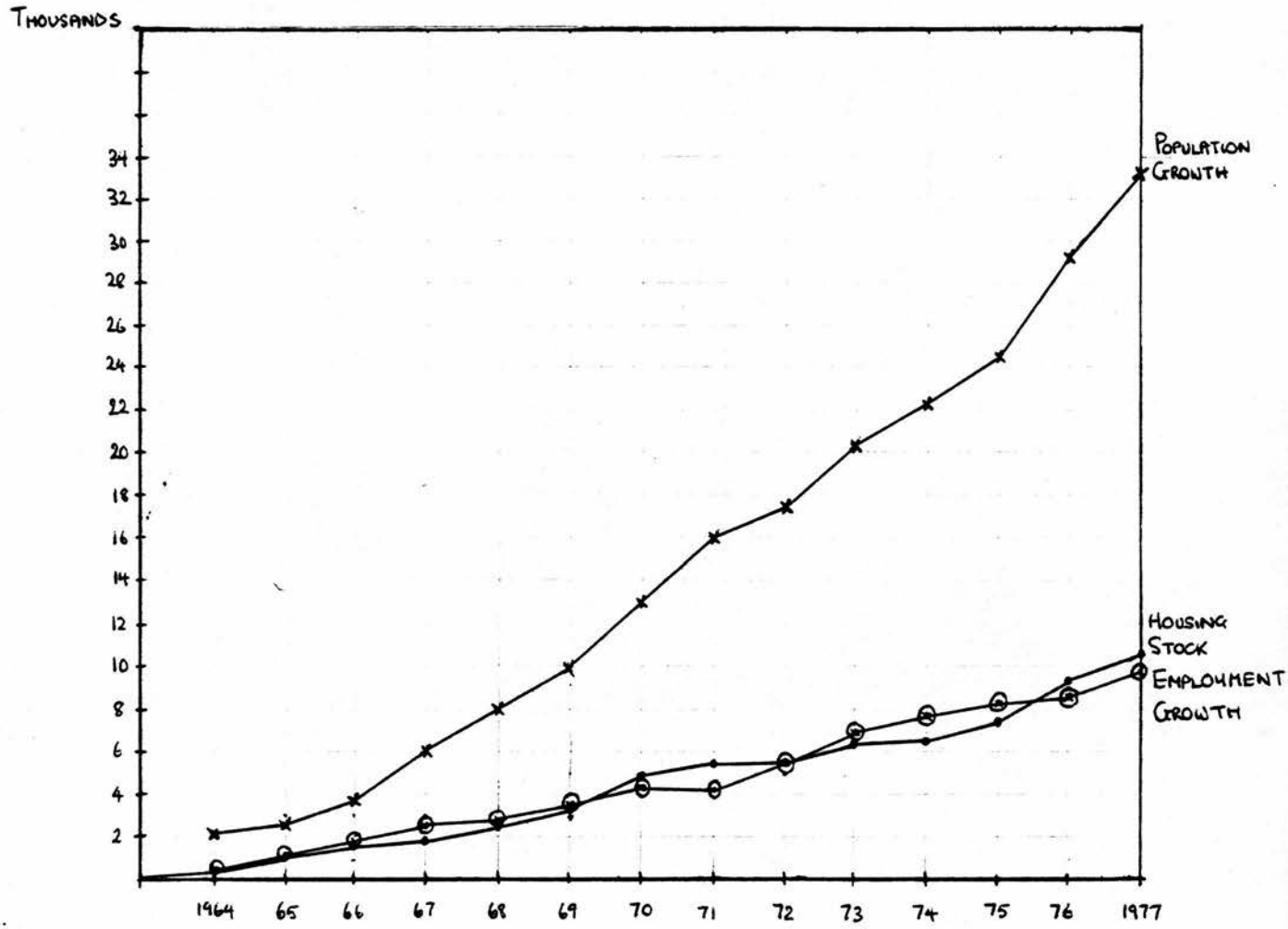
In the seventies it was the last aim that was given emphasis by the Governments focusing on the role of promoting economic growth. Indeed, although immigrants have come from all over Central Scotland, by the seventies Edinburgh was providing a larger contribution than Glasgow.

Since its designation Livingston has been Britains fastest growing New Town. From its initial population of 2000 it had achieved a more than seven fold increase by 1971, doubling again by 1977. The proposed target population is seventy thousand, with an allowance of thirty thousand for natural increase. By 1977 the population stood at 33,339 (see Fig. 3.3). No other New Town has grown as fast in the seventies, although some more recently designated towns starting from larger initial sizes have added more in absolute terms.

3.2 PHYSICAL STRUCTURE AND TRANSPORTATION

A start for Livingston New Town was provided by the expansion of the British Motor Corporations plant at nearby Bathgate with an initial target of a 5000 strong workforce. This development provided the first residents who were housed in the Deans area which already had the facilities and population of Deans Village and was expected to attract linking industries. Construction then followed an east to west pattern starting at Craigshill, which was completed in 1970 and is the most developed district, and then spreading to Howden and Ladywell. (see Fig. 3.4)

Fig 3.3


THOUSANDS
34
32
30
28
26
24
22
20
18
16
14
12
10
8
6
4
2
1964
65
66
67
68
69
70
71
72
73
74
75
76
1977
POPULATION GROWTH
HOUSING STOCK
EMPLOYMENT GROWTH



& AREAS UNDER CONSTRUCTION
PROPOSED RESIDENTIAL.
EXISTING INDUSTRY.
PROPOSED INDUSTRY
SCIENCE BASED INDUSTRIES
S.B. INDUSTRIES UNDERWAY
POTENTIAL INDUSTRIAL GROWTH AREAS.
COMMERCIAL DEVELOPMENT.
COMMERCIAL DEV. UNDERWAY.
▲ EXISTING HEALTH CENTRE
△ PROPOSED HEALTH CENTRE.
H PROPOSED HOSPITAL.
EXISTING PRIMARY SCHOOLS.
PROPOSED PRIMARY SCHOOLS.
EXISTING SECONDARY SCHOOLS.
PROPOSED SECONDARY SCHOOLS.
WOODLANDS.
OPEN SPACE.
GC PROPOSED GOLF COURSE.
EXISTING ROADS.
PROPOSED ROADS.
RAILWAY ROUTES.
DESIGNATED AREA BOUNDARY.
COUNTY BOUNDARY.
C COMMUNITY COLLEGE.

100 HA
1 KM

LIVINGSTON NEW TOWN PROGRESS PLAN

AS AT 31ST. MARCH 1975

Fig. 3.4



- CONSTRUCTION
- PROPOSED RESIDENTIAL
- EXISTING INDUSTRY.
- PROPOSED INDUSTRY
- SCIENCE BASED INDUSTRIES
- S.B. INDUSTRIES UNDERWAY
- POTENTIAL INDUSTRIAL GROWTH AREAS.
- COMMERCIAL DEVELOPMENT.
- COMMERCIAL DEV. UNDERWAY.
- EXISTING HEALTH CENTRE
- PROPOSED HEALTH CENTRE.
- H PROPOSED HOSPITAL.
- EXISTING PRIMARY SCHOOLS.
- PROPOSED PRIMARY SCHOOLS.
- EXISTING SECONDARY SCHOOLS.
- PROPOSED SECONDARY SCHOOLS.
- WOODLANDS.
- OPEN SPACE.
- GC PROPOSED GOLF COURSE.
- EXISTING ROADS.
- PROPOSED ROADS.
- RAILWAY ROUTES.
- DESIGNATED AREA BOUNDARY.
- COUNTY BOUNDARY.
- C COMMUNITY COLLEGE.

100 HA
1 KM

LIVINGSTON NEW TOWN

PROGRESS PLAN

AS AT 31ST. MARCH 1975

Fig. 3.4

The four main industrial areas were planned for the periphery of the town with direct access to the main motorways and sub-regional routes as shown on Fig. 3.5. The Kirkton Campus was designed to provide premises for scientific industrial developments with the main industrial development taking place in the Howden and Deans industrial estates.

Along the River Almond the central area was developed on an open space system, connected by segregated roads and footpaths to the rest of the town. With the opening of the Almondvale Centre shopping, office, recreational and educational facilities were provided (and in 1978 a bus station) for both the town and its sub-region. Before the opening of the Almondvale Centre in 1976 the shopping centre at Craighill served the needs of the population.

The physical structure of the town had as one of its fundamental determinants the requirements of vehicular traffic and pedestrian movement. The town was planned to allow unrestrained use of motor vehicles using a roughly rectangular grid system of primary distributor roads, which define the districts, enclosing residential districts each with a primary school and in the more outlying districts small shopping centres (see Fig. 3.6). The areas of development are, themselves, served by district distibutor roads.

Primary distributor roads are mainly dual carriageways and are designed to carry peak period traffic to the major employment centres and to provide for commuting both in and out of the town. They are also designed to provide routes for heavy goods vehicles serving the industrial areas, insulating them from residential development as much as possible, and thereby maintaining environmental standards by channeling through traffic from the local distributor roads.

Within districts the local distributor roads provide movement and routes for bus services and are designed to avoid attracting through traffic, by not providing a quicker route than the alternative town distributor roads. They also provide access to the main distributor roads from the single carriageway access roads which are in the form of cul-de-sacs, short loop roads, or parking roads.

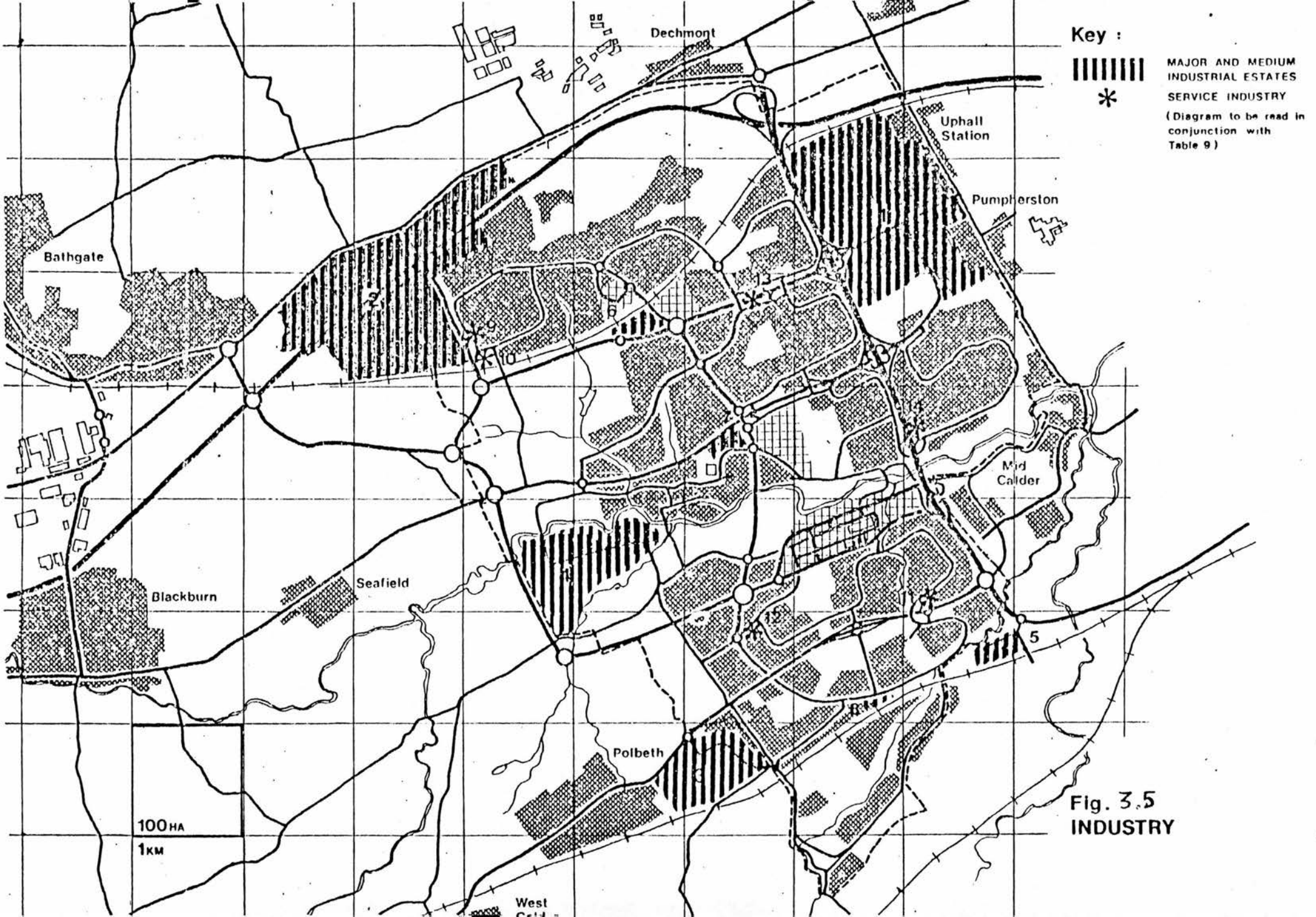


Fig. 3.5
INDUSTRY

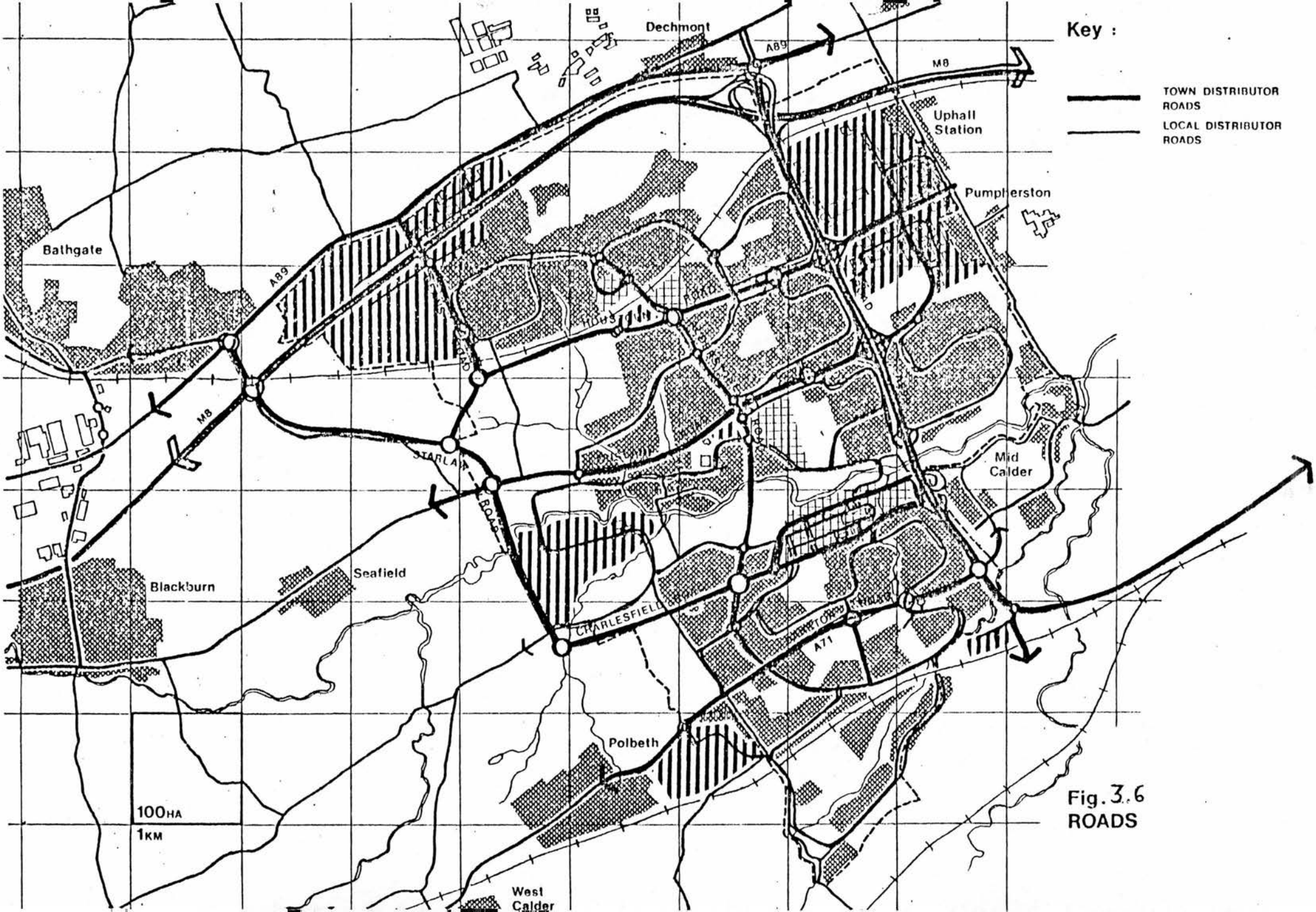

Key :
TOWN DISTRIBUTOR ROADS
LOCAL DISTRIBUTOR ROADS
Dechmont
A89
M8
Uphall Station
Pumpherston
Bathgate
A89
M8
Mid Calder
Blackburn
Seafield
CHARLESFIELD
A71
Polbeth
West Calder
100HA
1KM

Fig. 3.6
ROADS

The towns bus service is run by Scottish Bus Service (Eastern Scottish) together with the Lothian Regional Council. It was planned to bring the majority of dwellings within 400 metres of the bus stops and to allow all main journeys within the town to be undertaken by a single journey, with a radial network of sub-regional services, taking a relatively direct through routing. (see Fig. 3.7) In 1976 there were 16 bus routes of which 4 were internal and 12 were sub-regional. The opening of the bus station at the Almondvale Centre in 1979 made Livingston the centre of the sub-regional services.

Throughout the town there has been an established policy of traffic and pedestrian segregation which has operated effectively giving a low level of accidents involving pedestrians. The footpaths (Fig. 3.8) are designed on a rectilinear network allowing access to all parts of the town, with underpasses preventing the necessity of crossing major roads. The development of cycleways has been somewhat neglected, though they are proposed to be built along the main footpaths.

One omission from this otherwise impressive transportation network is rail travel facilities, though there are proposals to provide a rail goods and passenger link for Edinburgh and Glasgow by providing a station within Livingston. At present the only rail travel facilities are at stations outside the town.

3.3 SOCIOECONOMIC STRUCTURE

DEMOGRAPHIC STRUCTURE

The demographic structure of the New Towns represents one of their most important differences to the rest of the country and accounts for a lot of the variability between the New Towns themselves. The structure of the intrinsic population will have important effects upon development and planning both directly, through the requirement of varying amounts of age, specific facilities and indirectly, through the

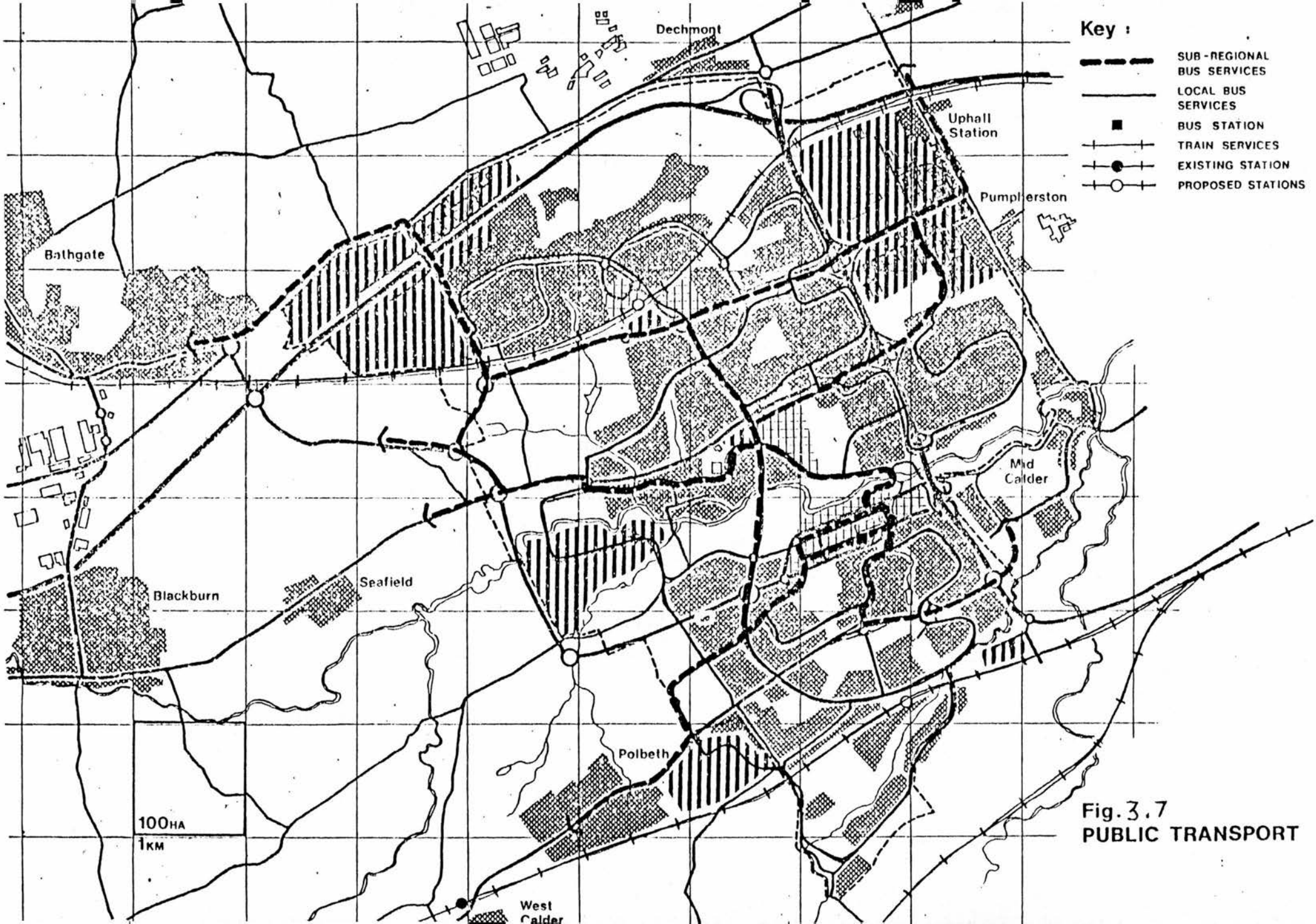


Fig. 3.7
PUBLIC TRANSPORT

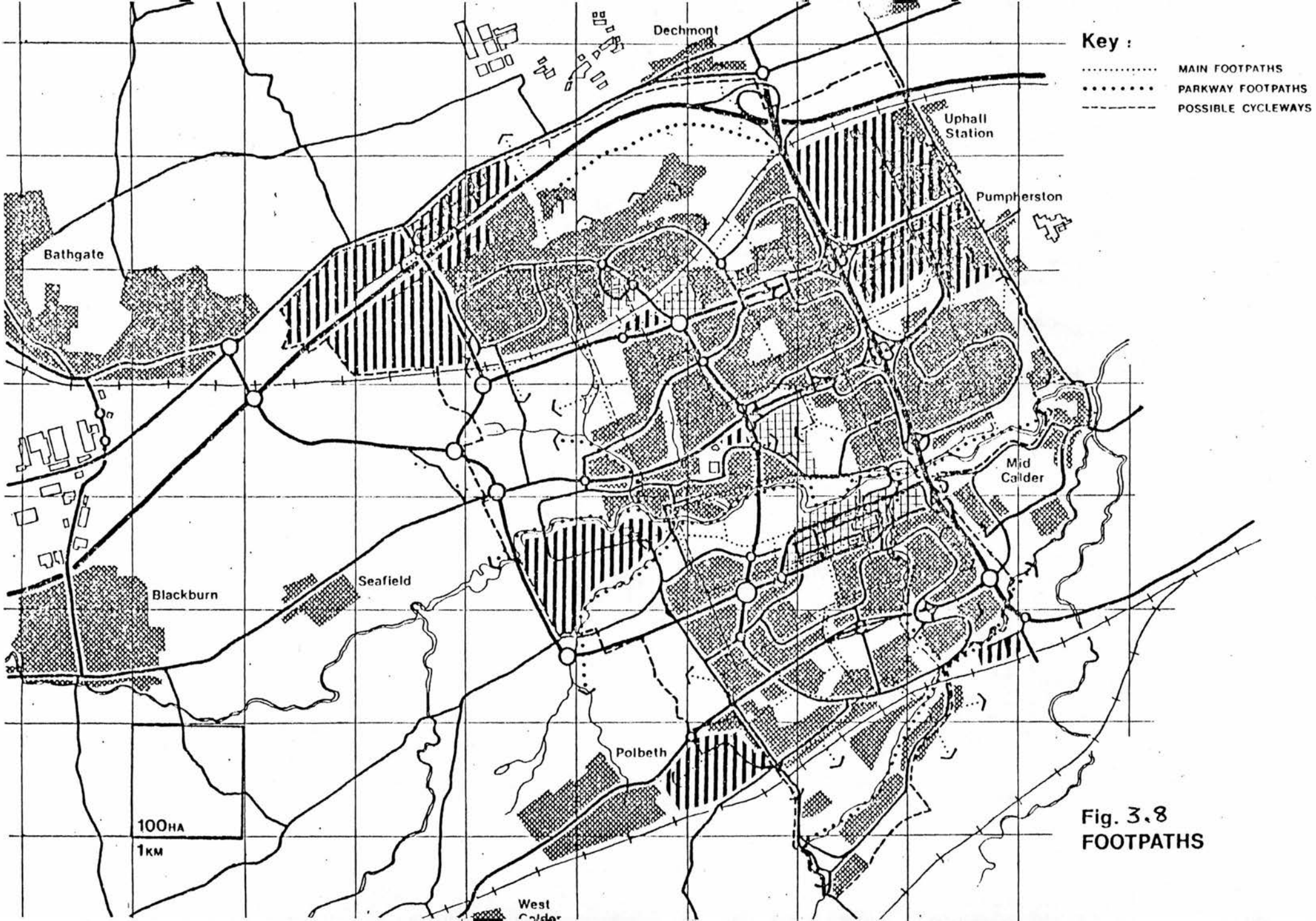


Fig. 3.8
FOOTPATHS

levels of overcrowding, economic activity rates and self containment. These features, together with various related socioeconomic factors will also affect the various aspects of travel demand such as car availability, levels of commuting and trip generation. It is thus worthwhile to consider the demographic features of Livingston both in the general New Town context and in comparison with the rest of the country.

In general the New Towns have shown very high rates of population growth, the total New Town population growing by 1,068,000 persons between 1951 and 1976, an increase of 124% compared with a national average of 13%. As can be seen in Table 3.1 the New Town population in 1971 was typified by a slightly higher proportion of males and a considerably younger population than the national average, the average median age being 29.1 compared with the national average of 34.2 and combined with a considerably lower proportion of retired people. Indeed there was a particularly noticeable difference in the 30 to 44 and under 10 age groups, probably reflecting the predominance of young married couples migrating to the New Towns and hence a high birth rate which again is reflected in the higher than national average household size.

Simply comparing the average values does, however, hide discrepancies between the individual New Towns which in some cases are very wide, but mainly related to the age of the town and the way in which its development was phased. It is noticeable in Table 3.1 that the Scottish New Towns averages for the reported demographic variables tend to reflect similar features, and indeed as a group show a more marked deviation from the national average than the New Towns as a whole. Irvine is closer to the national averages than its neighbours probably relating to its late designation from a large initial population.

Considering Livingston the differences in demographic structure when compared to the national averages are extreme indeed. Livingston had the most youthful population of all the New Towns, with the lowest median age, the lowest proportion over retirement age, one of the

DEMOGRAPHIC CHARACTERISTICS TABLE 3.1

	%GROWTH 1951-61	%GROWTH 1961-71	%MALES	MEDIAN AGE	%OVER RETIREMENT AGE	AVERAGE HOUSEHOLD SIZE
GB AVERAGE	0.5	0.5	48.5	34.2	16.2	2.9
NT AVERAGE	15.7*	5.8*	49.4	29.1	10.0	3.2
LIVINGSTON	0.0	20.7	50.0	23.3	4.3	3.4
EAST KILBRIDE	20.0	7.2	49.2	27.1	7.4	3.4
GLENROTHES	21.3	7.9	49.2	24.5	5.8	3.4
CUMBERNAULD	5.3	20.4	49.1	24.9	5.6	3.4
IRVINE	1.0	2.6	48.7	29.4	10.5	3.2
SNT AVERAGE	9.5	14.7	49.2	25.8	6.7	3.4

* Relates only to New Towns designated by the beginning of the period

NT=New Town
SNT=Scottish New Town

Source Champion,Clegg et al (1977)

highest proportion of males, and also one of the highest average household sizes. These features clearly relate to the town's high rate of growth (the highest of all the New Towns) from a small initial population.

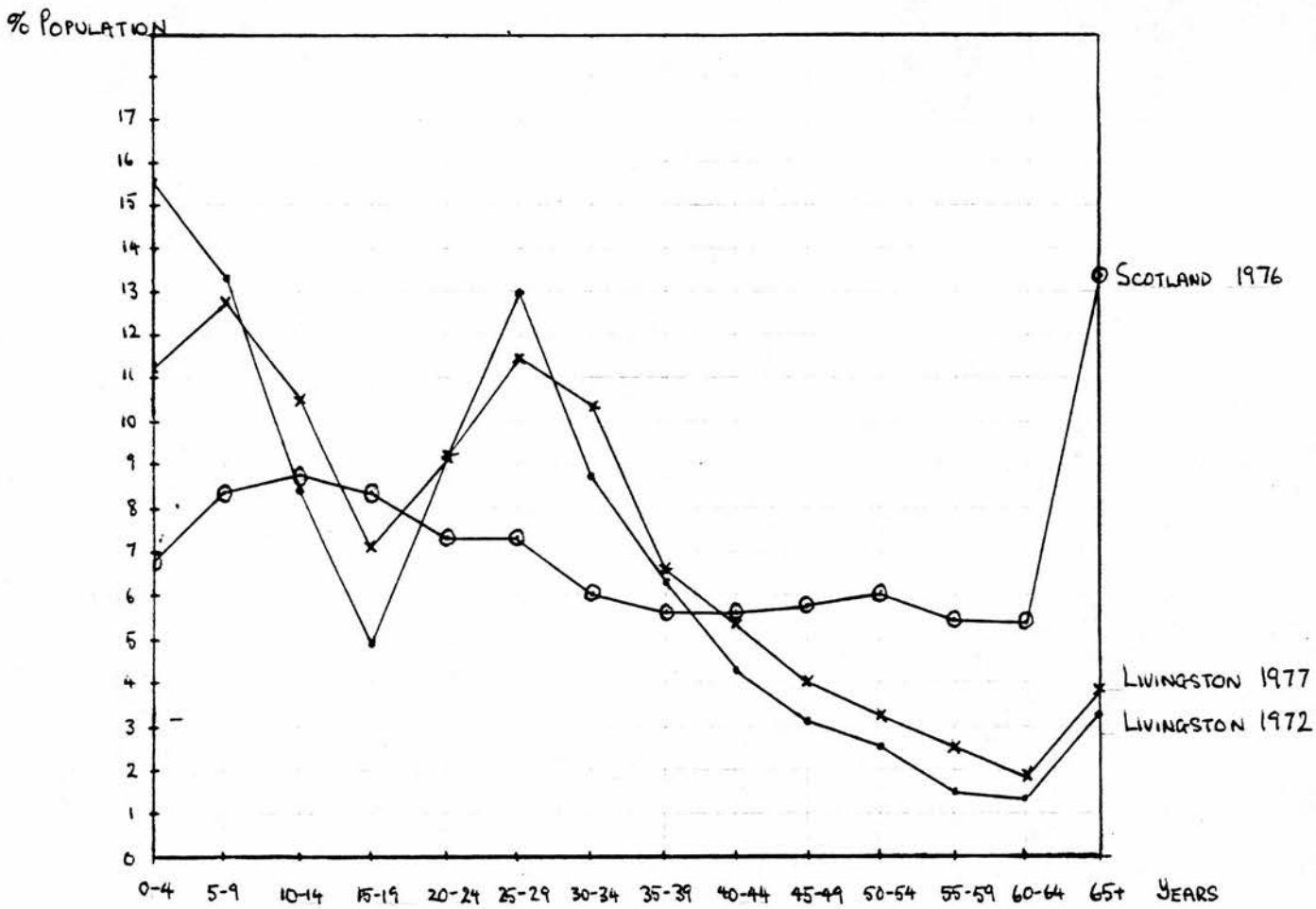
During the seventies, Livingston's population matured, though not significantly, towards the Scottish norm. Fig. 3.9 shows that in 1977 there was a very high proportion of 0-9 year olds, 23.9% as compared with the national average of 15.1%; 20 to 34 year olds, 31% as against 20.6% nationally; and only 5.8% in the above 60 year old range compared with a national average of 18.7%. The main maturing of age was as expected, in the older areas of the town, but this had not affected the figures for the whole town significantly by 1977, the average age for the town being only 23.4. If the 1977 situation is compared with that in 1972, however, it is clear that the age structure has, indeed, flattened towards the Scottish norm with the most significant increases being in the 60 plus and 10 -19 age groups (See Fig 3.9).

As would be expected, given the predominance of females of child bearing age, the birth rate within the town is higher than the national average, though it did fall in the seventies from 28 : 1000 in 1970 to 15.4 : 1000 in 1977, compared with the national average of 11.98 : 1000 in 1977. Again as expected, given the low elderly population, the death rate is correspondingly low.

Average household size did show a decrease in Livingston in the seventies, though it still remains much higher than the Scottish average. In 1977 it was 3.34 compared with the 1976 Scottish average of 2.9, reflecting a steady decrease from 3.53 persons per household in 1972. This decrease has been most significant in the range of households with more than five members and so is probably related to the decline in fertility which also took place with the maturing of the age structure. The composition of households showed a high proportion of families with young children, again related to the high household size, but again decreasing with the increasing maturity of the population and the implied shedding of dependants by households.

Age Structure

Fig 3.9



Champion, Clegg and Davies (1977) consider that the New Town demographic figures illustrate a sequential development of the town from the date of designation.

1. Close to the national norm before development, although this will depend on the initial population.

2. Increasing youthfulness resulting from a flow of young couples into the town. This will be especially marked when there is a small initial population, as at Livingston, giving high average household size and low median age.

3. The further in-migration of young people is countered, to some extent by the aging of the existing population.

4. The end of the rapid build - up is reached, though the population is still youthful.

5. There is a move towards the national norm as the population matures.

These stages, which typify New Town growth, will represent the development of any expanding settlement which is dependent on young in migrants, especially young married couples. Variations which exist between the New Towns, in terms of their classification to the various stages will be the result of differences in the speed of increase of the population and the initial population of the town. Further in all towns with such development paths it will be the scale and pace of the developments that will cause the main planning problems for the provison of age specific facilities. Clearly such facilities will be required in large quantities and certain stages of development but will become underutilised as the demographic structure tends towards the national norm.

In Livingston the small initial population was neither close to the national, nor the Scottish norm in terms of its demographic features

because of the depressed nature of the region. This together with the extremely high growth rate and the aforementioned extreme age structure made the problem of planning facilities extremely difficult. As with other New Towns, further problems were created by imbalances within the town, with districts tending to represent a microcosm of the New Town development stages. Indeed even as the towns population tends towards the national norm the same stages and inherent problems may still occur within the town itself, especially when, as in the case of Livingston, development of the residential areas takes place sequentially and the predesignation population is low.

3.4 HOUSING

The structure of housing within the New Towns represents an important distinction between them and the nation as a whole. Clearly housing characteristics will be related to the demographic structure of the towns and a lot of variation between the New Towns will be dependent on the date of designation. There are also, however, significant regional differences.

As can be seen in Table 3.2 the New Towns in 1971 had a much larger proportion of publicly rented housing compared to the national average, resulting from the important role of the Development Corporations in construction. They also had a higher than national average proportion of the population with access to three basic amenities, which relates to the level of development planning and the low proportion of old housing inherited at designation (although this is dependent on the size of initial stock). The relatively high density of persons per room, shown by the New Towns, relates mainly to the demographic structure of their populations, with its plethora of young families, although the typical New Town development does tend to have a small average house size. In the more mature towns the decrease in household size resulting from the maturing of the population led to decreased density.

These features were clearly more distinct in the Scottish New Towns which showed the highest proportion of publicly rented housing, along

HOUSING CHARACTERISTICS TABLE 3.2

	%PUBLIC RENTED	%WITH 3 BASIC AMENITIES	ROOMS PER HOUSEHOLD	%WITH 4-6 ROOMS	PERSONS PER ROOM
GB AVERAGE	31.6	82.5	4.8	74.8	0.6
NT AVERAGE	64.0	92.6	4.8	80.0	0.7
LIVINGSTON	91.9	100.0	4.8	84.8	0.8
EAST KILBRIDE	82.3	99.7	3.8	59.8	0.9
GLENROTHES	84.8	99.8	4.0	66.3	0.8
CUMBERNAULD	82.2	99.4	4.2	77.8	0.8
IRVINE	80.6	95.1	4.0	63.3	0.8
SNT AVERAGE	84.4	98.8	4.2	70.5	0.8

NT=New Town
SNT=Scottish New Town

Source Champion,Clegg et al (1977)

with North England, although this does relate to the higher proportion of publicly rented housing overall in these regions, especially in Scotland. It is interesting that those towns which have the highest fertility seem to have the smallest houses, a feature which led to the aggrevation of pressures on the existing household stock.

Livingston illustrates these discrepencies in a more extreme form than the Scottish average. It had the highest percentage of publicly rented accomodation and the highest proportion with access to the 3 basic amenities of all the New Towns, together with the highest rooms per household of all the Scottish New Towns, although the Scottish New Town average was lower than the overall New Town and the national averages. Further, Livingston had the lowest number of persons per room of the Scottish New Towns, although, again, this figure was substantially higher than both New Town and national averages.

These features of high quality housing stock and the vast majority of housing publicly rented remained a distinctive feature of Livingston in the seventies. There was, however, a significant increase in the number of private house buildings and tenant sales with 8.4% of all dwellings being owner occupied by 1977.

This new private sector with 2326 inhabitants in 1977 differed from the town as a whole in demographic characteristics having fewer individuals in the extreme age groups, below 25 years and above 50 years, a lower household size of 3.17 and a larger proportion of childless married couples. These differences were to be expected for a number of reasons. The housing in the private sector was predominantly of a type suitable for first time buyers, which was reflected in the lack of higher age groups and the large proportion of households who had resided in rented accomodation in Livingston.[1.] The small number of under twenty fives and the large proportion of childless married couples would appear to reflect the middle class nature of the owner occupiers in terms of late marriage, family planning and other such features, as well as the difficulties of getting a mortgage. In addition to the private sector

1. Although the low age of immigrants would influence this.

there were 338 sales of Corporation houses to their occupiers by 1977. These households were predominantly younger than the average for rented houses with a slightly lower household size than the towns average of 3.34 in 1977.

Another minority group which differed markedly from the town as a whole were the estimated 1054 persons who in 1977 were still living in the 393 houses built before designation. These households were predominantly of the older age groups with more single and two person households than the town as a whole, 44% being over 45 years of age as compared with 16% overall, 41% of these female and 50% over retirement age. These households clearly represent the established mature populace in the older housing, the extreme differences resulting from the depressed nature of the predesignation area with its high level of migration, composed mainly of the younger persons, leaving the older age groups and pensioners in the area.

Corporation rented housing was at a level of 7936 dwellings by 1977, occupied by an estimated 27,920 persons with an average household size of 3.5. As these accounted for more than 90% of the total housing stock the characteristics of the inhabitants were clearly the dominant ones for the whole town. There were, however, variations across the three types of dwelling available within this category.

Flats, which made up 18.4% of the rented housing stock in 1977, housed a majority of the households to which they were best suited, namely single, childless married and retired. 20% of those people living in flats were single householders compared with 8% for the whole town, while household size was much lower at 2.47, with a large proportion of the younger adult age groups. There was however 16% within the four years old or less age group, indicating the development of potential transfers to non flat accomodation.

Within the standard rental housing which comprised the majority of the housing stock (69.4%), there was a predominance, not surprisingly, of

young families with 21.4% within the 25 - 34 years age group and an average household size of 3.6. This is in contrast with the higher rental stock which composed 12.2% of the total and was predominated by more mature households with teenage children. Within this group there was a high proportion of adults between the ages of 35 and 39 and the average household size of 3.73 was the highest of all the groups, probably because the more mature families were composed of more dependents over a wider age range.

Livingston Development Corporation, clearly, did not inherit the problem of sub-standard pre-designation housing which affected many of the New Towns which started from large initial populations. It did, however, encounter the problem of overcrowding relating to the small size of Development Corporation housing and the high level of fertility. This problem, however, tends to decrease as the population matures and household size diminishes. Although problems of under-occupation can occur if the future demand for small houses is not anticipated. Certainly, as with most New Towns, the level of single person accomodation is at present low.

Although the situation has improved, Livingston still faces the common New Town problem of lack of owner occupied property. This can create problems of attracting certain socioeconomic groups to the town and cause the migration of those upwardly socially mobile families to the surrounding areas, affecting both the social mix and the commuting patterns of the town. However, despite Livingstons extremely low level of owner occupied housing, when compared with the national or New Town averages, the problem can be considered less important because of the regional context. This follows from the fact that Scotland in general has a high level of publicly rented accomodation implying less conciousness of the middle classes to housing type.

3.5 EMPLOYMENT

Employment in the New Towns shares with population and housing a distinctive rate of growth as compared to the national average. It

should, however, be borne in mind that the 1971 figures were compiled before the recession of the national economy in the mid -seventies, a fact which must clearly be taken account of in analysing developments.

In 1971 the New Towns achieved higher than national average activity rates in all the categories presented in Table 3.3, each being at least 5% greater than the national average. This is partly due to the lower average proportions of retired persons in the New Towns, although even when age is taken into account the rates are generally higher. There were also differences in activity rates between the New Towns which correlate closely with the age of the New Town population, the size of the initial population and their regional setting. These regional discrepancies were most marked for the unemployment statistics, with only two of the ten New Towns with the lowest unemployment rates being situated outside the south east of England.

Female activity rates also showed some regional disparity with the Scottish New Towns tending to be lower, on average, than the New Town average, possibly related to the high fertility of these towns, although they were still above the national average. Further the Scottish New Towns showed higher than national and New Town average male activity and unemployment rates with Livingston representing the extreme of all these features. Indeed as well as having above average male activity and below average female activity rates, Livingston had in 1971, one of the highest unemployment rates of all the New Towns. These features are clearly related to the low average age of the population and the high proportion of young mothers (emphasised by the low, relative to New Towns, activity rate for females of 15 or more years) giving female activity rates close to the national norm despite the small proportion of retired persons.

One apparent feature of the analysis of activity rates is the regional variation between the New Towns, especially apparent when considering the Scottish New Towns in contrast to the New Town average. This further underlines that in analysing the socioeconomic structure of Livingston its regional context must be taken into account, as although

EMPLOYMENT -ACTIVITY RATES 1971

TABLE 3.3

ECONOMIC ACTIVITY RATES

	MALES 15+	FEMALES 15+	MARRIED FEMALES 15+	MARRIED FEMALES 35-9	UNEMPLOYMENT RATE
GB AVERAGE	81.4	42.8	42.2	53.9	4.0
NT AVERAGE	86.7	47.7	47.3	60.1	4.2
LIVINGSTON	92.0	44.9	42.1	54.6	7.6
EAST KILBRIDE	87.1	51.5	51.3	64.4	4.1
GLENROTHES	89.1	46.2	44.2	55.3	5.9
CUMBERNAULD	90.1	47.1	46.6	59.2	6.5
IRVINE	85.0	42.2	39.6	50.7	4.8
SNT AVERAGE	88.7	46.4	44.8	56.9	5.8

NT=New Town
SNT=Scottish New Town

Source Champion,Cleas et aL (1977)

representing many New Town features in an extreme form Livingston's divergences from the Scottish New Towns were much less marked.

These features which in many ways reflect the immaturity of Livingston as a New Town continued through the 1970s. By 1977 there were 8903 permanent jobs (excluding construction) in Livingston with 43.6% of the population working or registered unemployed. This was higher than the 37% in 1972 but still less than the 1976 Scottish average and, when combined with the substantially higher than national average male/female ratio, would appear to reflect the high proportion of mothers with young children reaching school leaving age (both features of the maturing of the towns population).

It is worth considering that the increase in female activity rates would appear to illustrate, a point made by Thomas (1969), that New Towns have tended to be most successful in providing female employment. This results from the decrease in journey to work distances which opens up the possibility to the less spatially flexible (because of household and family commitments) female populace. This point is further supported by women being more evident in part time employment and the trend of decreasing male/female ratio, as compared to the Scottish average, both implying a lower proportion of career women within the workforce despite the evident increase in the proportion of women working.

Livingstons' high level of registered unemployed in 1971 (7.6%) had increased to 9.2% by 1977 (an increase of 3.3% over the 1972 figure). Though these figures are high for a New Town, when compared with the regional figures of 7.4% for the Lothian Region and 8.9% for Scotland, the implications for Livingston are not so extreme. Indeed, it might be considered to highlight the speed with which Livingston had fitted into its regional context, a feature shared by the other Scottish New Towns. Further, a large proportion of those unemployed for reasons other than redundancy and sickness, 57.5% of the unemployed in 1977, were school leavers with 19.4% of the 16 -19 year old school leavers who were available for employment being unemployed.

These features probably relate to the fact that industry was not geared to accepting the young especially when it could attract older skilled workers. Indeed the peak of school leavers occurred in the mid 1970s recession and, with very few vacancies created by retirement, were difficult to absorb. Although in 1977 22 of the 86 industrial firms provided apprenticeships, the demand for them was high and, hence, they were difficult to get. The features of industry geared to use migrating skilled workers together with a low proportion of clerical and unskilled jobs available, clearly made the job search process for school leavers difficult.

Information on the previous occupations of Livingston's registered unemployed, in 1977, reflected the fact that the employment structure of the town was deficient in clerical and service work. The labour markets for such employment, especially before the opening of the Almondvale Centre, existed only outisde the town. Thus, it might be expected that there was a high level of female quits on moving to the town, the move being influenced by the male householders job prospects. Although the situation did improve in the 1970s, as shown by the activity rates, this potential supply of labour is not reflected in the unemployment statistics as many will not register, but take work if offered it. Therefore this feature could be more widespread.

In general, Table 3.4 shows the employment structure of the New Towns to have a distinct bias towards manufacturing industry. This partly reflects the use of New Towns to take the overspill from older industrial conurbations which were being redeveloped. Clearly, the resulting migrants had a high proportion of manufacturing skills, meaning that manufacturing industry could be attracted by the availability of such labour. The more recently designated New Towns, however, with their emphasis on aiding regional development have shown less manufacturing bias.

The distribution of the workforce in the New Towns differed from the resident population only in special circumstances and in the cases of selective commuting. Some of the towns, created to take overspill,

EMPLOYMENT STRUCTURE 1971

TABLE 3.4

	EMPLOYED RESIDENTS			JOBS PROVIDED-WORKFORCE		
	MANUFACT	CONSTRUCT	SERVICES	MANUFACT	CONSTRUCT	SERVICES
GB AVERAGE	34.3	7.0	53.6	34.3	7.0	53.6
NT AVERAGE	47.6	7.0	43.5	48.7	7.7	42.0
LIVINGSTON	39.1	11.8	48.0	45.8	16.1	36.6
EAST KILBRIDE	45.1	6.0	48.5	49.1	4.9	45.2
GLENROTHES	42.7	9.7	42.2	55.5	6.2	37.3
CUMBERNAULD	36.1	7.1	56.2	46.6	11.5	43.5
IRVINE	50.9	11.5	37.2	48.2	10.5	38.7
SNT AVERAGE	42.8	9.0	46.4	49.0	10.0	40.3
SCOTLAND 1975				30.8	8.3	56.8
LIVINGSTON						
1972	37.6	9.4	52.2			
1975				57.8	0.7	41.5
1976				54.4	1.3	41.5
1977	40.3	5.0	53.6	49.5	1.3	47.0

NT=New Town
SNT=Scottish New Town

Source Champion,Clegg et al (1977)
Livingston Household Survey Reports
Livingston Employment Survey Reports

showed stronger manufacturing emphasis in the workforce than in the resident population, implying out commuting of service workers and possible in commuting of manufacturing workers. This was apparent in both Livingston and Cumbernauld in 1971, with the Scottish New Towns as a whole showing the same features, with their imbalance between workforce and the employment of residents and the bias towards manufacturing being greater than that of the New Towns overall.

In general, although there were wide discrepancies between the New Towns as a whole, they can be considered to have been successful in providing employment and to some extent achieving their original goal of self containment, at least by comparison with traditional dormitory towns. The goal of self containment has, however, been more prominent in the plans of the older New Towns and hence it is these towns which have been most successful in attaining it. The creation of employment was most successful in those New Towns with isolated provincial sites, as illustrated by the success of the Scottish and North East England developments. Indeed it was this success which influenced the further use of New Towns to rejuvenate local depressed regions by acting as growth centres.

Another area of success, as previously mentioned, has been the increasing of female activity rates and hence the more efficient use of potential labour supply. Indeed this was an explicit aim in some New Towns, intended to be realised by such developments as the reduction of work travel time.

Problems have developed, however, mainly resulting from the national economic depression in the seventies and the age imbalance within the towns, creating a lot of school leavers but few vacancies. This problem was aggravated by the concentration of New Towns on manufacturing employment, which has been a declining employer, coupled with the failure of many New Towns to provide service employment and the branch nature of many industrial developments in New Towns (although this was a wider regional problem).

The structure of employment in Livingston showed a similar discrepancy to the rest of the country as did the Scottish New Towns as a whole. Again there was a bias towards manufacturing employment but with an especially large shortage of jobs for service employed residents, and a larger proportion of construction employment. These features relate to the recent designation of the town, implying a high level of construction work and the importance of the towns regional links, especially with Edinburgh in providing service and professional employment.

During the seventies the proportion of service employment provided within Livingston rose drastically from 36.6% in 1971 to 47.0% in 1977, while construction employment dropped sharply and manufacturing, though higher in 1977 than in 1971, showed a continued steady decline from previous levels (Fig. 3.10). The employment of the towns residents increased in both manufacturing and services, declining in construction (Fig. 3.11) meaning that the imbalance between residents occupations and jobs available, though decreasing for service industries quite significantly, still remained at a high level, while increasing for manufacturing.

Comparing these figures with those for Scotland in 1975 (Fig. 3.12) illustrates that the jobs provided in the service and construction sectors were still well below the Scottish average and those in manufacturing well above. This difference with the Scottish average of higher manufacturing and lower service employment probably reflected the lack of small service operations in Livingston at that time. This mainly resulted from the difficulty of getting small relatively cheap premises, which would have impeded the setting up of such operations.

In general the discrepancies between the jobs provided in Livingston and the type of employment of the residents highlight the role of the town within the regional market, both in the provision of homes for the workers outside Livingston and the provision of jobs for those resident outside the town. Further the dearth of service sector jobs within the town, although improved by the opening of the Almondvale Centre in

EMPLOYMENT

Fig 3.10

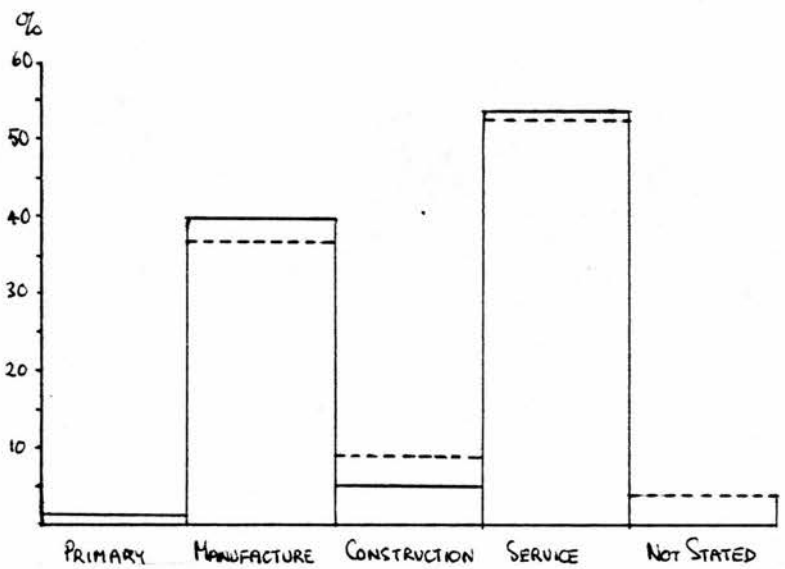


Fig 3.11

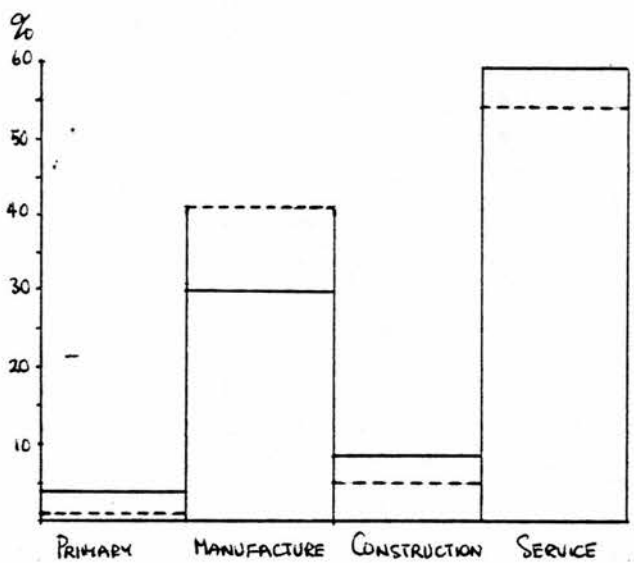
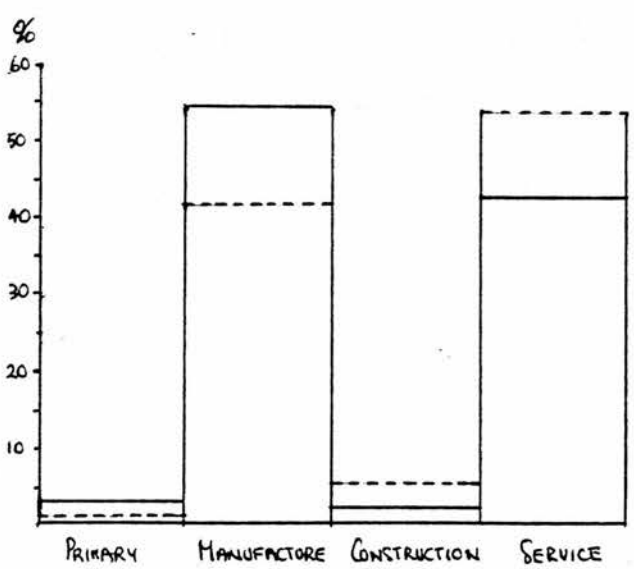


Fig 3.12



1976, illustrates the importance of Edinburgh as a provider of service and professional employment and, as shall be seen, the importance of commuter work journeys for the town.

3.6 SOCIAL STRUCTURE

As was seen in the previous chapter, the social composition of New Towns has been an important consideration in their development planning. All New Towns have tried to achieve some form of social balance, by attempting to accommodate the whole range of social groups, prevent internal segregation and thereby preclude the usual town growth pattern of single class dormitory suburbs or council housing estates. This concern stemmed from both ideological and practical considerations. The former being the aim of providing balanced communities with New Towns taking their fair share of the lower classes and the latter the necessity of a wide range of social groups to attract a wide range of cultural and social amenities. A New Town without middle class residents might have difficulty in attracting such amenities.

The actual aim of social balance is, however, not clear cut and has no precise definitions or fixed terms of reference. This has led to a number of pragmatic interpretations such as achieving a social mix comparable to the nation as a whole, although it might be argued that towns of a similar size would present a more accurate yardstick. The usual criteria for measuring, or analysing, the degree of social mix such as housing amenities, overcrowding and tenure problems are clearly not so important within the New Town context. Thus, any such analysis must be based upon the socioeconomic groupings within the town and such features as car ownership, educational qualifications and income levels.

Table 3.5 illustrates that in 1971 the New Towns had a higher level of skilled manual workers than the national average with a below average proportion of non manual workers. This feature clearly relates to the employment patterns in the New Towns, namely the emphasis on

SOCIOECONOMIC CHARACTERISTICS TABLE 3.5

	ECONOMICALLY ACTIVE MALES			HOUSEHOLD		NO. EMPLOYED
	%NON MANUAL	%SKILLED MANUAL	%OTHER MANUAL	%WITH NO CAR	%WITH 2+ CARS	%WITH A LEVEL LEVEL,DEGREE OR EQUIV
GB AVERAGE	34.8	38.9	23.0	49.0	8.7	15.2*
NT AVERAGE	32.1	42.4	23.7	44.6	6.4	19.2*
LIVINGSTON	31.7	45.2	21.6	41.1	4.5	32.4
EAST KILBRIDE	44.7	38.5	15.7	43.4	5.3	30.3
GLENROTHES	33.5	43.9	20.8	38.1	5.0	32.1
CUMBERNAULD	37.8	40.6	20.1	48.9	8.4	32.1
IRVINE	25.4	44.1	28.7	56.6	3.9	19.4
SNT AVERAGE	34.6	42.5	21.4	45.6	5.4	29.3
SCOTLAND REGIONAL AV.	31.0	39.4	26.5			
GB REGIONAL AV.	34.8	38.9	23.0			

* Not comparable because differing Scottish education system

NT=New Town
SNT=Scottish New Town

Source Champion,Cless et al (1977)

manufacturing industry, with low non manual workers because of the low level of owner occupied housing and possibly selective out migration to surrounding regions by promoted workers. The level of car ownership was also higher than the national average 0.65 cars per household in 1971 compared with 0.61 for the national average, and further reflected in the lower proportion of carless households in the New Towns, 49.1% as opposed to the national average of 42.2%, and a resulting lower proportion of households with two or more cars. Although the figures on qualifications are of limited usefulness, because of the differing educational systems, the New Towns do appear to have a higher level of education than the national average. Such a feature is, indeed, intuitively plausible, given the low average ages of the New Towns which would offset the low proportion of non manual workers.

In general it would appear that these results contradict the criticism that New Towns have not taken their fair share of the lower classes. Further they appear to some degree, though not equally, to have achieved social balance despite clear regional variations.

Comparing the average values for Scottish New Towns with both the New Town averages and the national averages is made difficult by the clear differences between the individual towns. Although the proportion of non manual workers in the Scottish New Towns is on average closer to the national average than the New Town average, this comparison hides the very large representation of this group in East Kilbride, which has the smallest proportion of skilled/semi skilled manual workers of all the New Towns, and the very small representation in Irvine. Bearing the range of values of the individual towns in mind, the Scottish New Towns did appear to have a similar proportion of skilled manual workers to the New Town average, with a lower proportion of other manual workers. They also appear to have a slightly higher level of non car owning households than the New Town average, although still lower than the national average.

As regards Livingston, the socioeconomic groupings showed, in 1971, the New Town pattern in its extreme form, with a very high proportion of

skilled manual and a lower than both national and New Town average, proportion of non manual workers. Similarly with car ownership Livingston had a much lower proportion of non car owning households and a much lower proportion of households with 2 or more cars, implying an even more extreme concentration of one car owning families than the general New Town level. Livingston also had one of the best records as regards qualifications, although the difference between the educational systems in Scotland and England must be taken into account.

Such features tend to reflect the degree of regional integration of Livingston, with any divergences from the surrounding region relating to its New Town characteristics. The high level of education and high car ownership were closely influenced by the population age structure and the close links with Edinburgh. Table 3.5 illustrates, by comparison with the Scottish socioeconomic groupings, both the regional effects and the disparities caused by Livingston New Town characteristics.

Within Livingston there are socioeconomic and demographic differences between the different areas, most markedly between predesignated areas and the newly developed areas, with the inherited population having lower car ownership, educational levels and obviously lower age. There are also wide differences between the town and private sector. This problem of internal variation is common to all of the New Towns and generally related to date and phasing of development, and the predesignation population. The later in migrants tending over the years to be better off than the original populace.

3.7 COMMUTING

Commuting patterns, together with in migration, are important aspects of New Town developments, being closely related to the underlying goals of this form of development. The archetypal New Town might be considered to receive families from the conurbations and provide them with housing and employment in situations where work journeys are minimal and the supply and demand for labour balanced. In the early

New Town developments, especially around London, this goal of "self containment" was an important aspect of plans to accommodate the overspill in the New Towns. As has been seen, however, the development of New Towns to provide growth centres to rejuvenate depressed regions meant the achievement of balance within the town lost its immediate importance.

Considering the situation in 1971, using indices of self containment and job/worker balance (Table 3.6), it is clear that although the New Town had achieved high levels of balance and self containment, most New Towns acted as employment centres with job ratios greater than one[1]. All of the Scottish New Towns, however, had job ratios of less than one, the extremes being Livingston and Cumbernauld where there were only 2 jobs for every three workers. The towns with such features tended to be those with large employment areas locally.

The degree of self containment of the New Towns differed, as regards commuting levels, with some New Towns with job ratios close to unity (and henceequality of jobs and employed residents) appearing to be less self contained in terms of commuting levels, than New Towns which were employment centres dependent upon surrounding areas for labour. It was Livingston that provided the most extreme commuting levels, for although it provided only 68% as many jobs as it had employed residents 46.6% of these jobs were taken by people resident outside the town, meaning nearly 64% of the towns residents commuted from the town to work.

Livingstons extreme lack of self containment reflected its proximity to Edinburgh where, in 1975, just over 20% of the residents were employed as well as its role as a focal point for regional growth. Indeed although commuting patterns might be seen to imply the success of the town in its role as a growth centre, the lack of service employment in Livingston and the large proportion of service and professional workers within the group commuting to Edinburgh must be considered. This further illustrates that although it was the larger New Towns that

1.The ratio of jobs available to residents employed. If greater than one, a net inflow of labour is indicated.

JOB BALANCE AND COMMUTING TABLE 3.6

	JOB RATIO	INDEX COMMUTING INDEP	IN COMMUTERS (1)	OUT COMMUTERS (2)
NT AVERAGE	1.0	1.2	33.6	32.8
LIVINGSTON	0.7	0.4	46.6	63.5
EAST KILBRIDE	0.9	0.8	34.5	40.7
GLENROTHES	0.8	0.7	35.3	45.0
CUMBERNAULD	0.7	0.4	41.5	60.7
IRVINE	0.8	1.1	24.4	35.5
SNT AVERAGE	0.8	0.7	36.5	49.1

(1) As a percentage of the workforce
(2) As a percentage of employed residents

NT=New Town
SNT=Scottish New Town

Source Champion,Clegg et al (1977)

Job ratio= ratio of employment to residents= $\frac{\text{employment level in town}}{\text{no. residents in employment in area}}$

index of commuting independence= $\frac{\text{journeys within an area}}{\text{journeys in + journeys out - crossing journeys}} = \frac{\text{local journeys}}{}$

$= \frac{\text{residents who also work in the area}}{\text{residents working outside + persons employed in area living outside}}$

$= \frac{\text{internal journeys}}{\text{commuting in + commuting out}}$

This has maximum value if no journeys by residents to places outside

appeared more self contained the regional situation and hence the proximity to conurbations, as illustrated by Livingston together with Cumbernauld, is of prime importance.

By 1977, 57% of the jobs available in Livingston were filled by residents, with only 41.2% of the towns employed population having jobs in the town. Of the remaining 58.8%, 35.3% travelled to Edinburgh and 40.9% were employed in the Livingston sub region. Although there was little change in the level of out-commuting from 1972 (Table 3.7) there was a shift away from Glasgow and the West towards Edinburgh and the Livingston sub region, possibly resulting from the parallel change in the origin of the population.

In 1977 the majority of out commuting occurred in Food, Drink and Tobacco, Mechanical Engineering, Vehicle and Construction Industries, with in particular 85% of the residents employed in vehicle manufacturing commuting to Bathgate. However, the commuting patterns are clearer when the commuters occupations are considered. The predominant ones were:

Professional and Technical where 47% commuted to Edinburgh
Engineering and Allied where 30% commuted to Bathgate
Clerical where 60% commuted to Edinburgh

The Bathgate figures reflect the importance of the British Leyland plant in that town, indeed one of the original purposes of Livingston was the provision of housing for the proposed increase of the workforce. As regards Edinburgh, the important role played by the level of service and technical employment there, is as clear as its underepresentation within Livingston.

Within Livingston the proportion of out commuters varied from district to district as a result of such factors as the unemployment patterns existing prior to designation, the role of Livingston in the regional housing market and the origins of the residents. The private area Murieston showed an especially high proportion of out commuting both

COMMUTING FLOWS

TABLE 3.7

IN COMMUTING	1975	1976	1977	
WITHIN LIVINGSTON	54.7	56.0	56.0	residents employed in Livingston as a percentage of workforce
OUTSIDE LIVINGSTON	45.3	44.0	44.0*	in-commuters as a percentage
EDINBURGH	5.5	6.1	6.0**	of workforce

OUT COMMUTING	1972	1977	
WITHIN LIVINGSTON	41.2	41.2	residents employed in Livingston as a percentage of employed residents
LIVINGSTON SUB-REGION	22.9	24.7	residents employed elsewhere as a percentage of employed residents
ELSEWHERE	35.9	34.1	" "
EDINBURGH	21.5	21.5	

** approximate figure as Employment Survey 1977 quotes only rest of Lothian (7.5%)
* 1971 outside Livingston category 46.6%

Source Livingston Employment Survey Reports
Livingston Household Survey Reports

to Edinburgh and the sub region, as compared to the town as a whole. This might imply some imbalance in higher income jobs, or more in commuting to higher income jobs within Livingston.

It is clear that the Livingston development cannot be viewed in isolation from its sub region. The above results indicate that the town's role as a focal point for regional growth has clearly required the aim of "self containment", certainly as regards work journeys, to be overshadowed by the desire for balanced commuting and high employment levels. The importance of the town within its sub region and its links with Edinburgh are clearly apparent, although as the towns population increases and service industries are developed it is to be expected that the imbalances will become less marked.

3.8 MIGRATION

As would be expected, given the phasing of development of the New Towns, nearly all of them showed positive migration balances with the rest of the country between 1966 and 1971. The level of migration was clearly related to both the stage and size of of the development of the individual towns, with most of the out migration average of 16.3% of the 1966 population being from small New Towns in problem regions. (Table 3.8)

The Scottish New Towns showed a much higher level of in migration as compared to the New Town average, with slightly higher out migration. This gave a net migration figure three times larger than the New Town average. The main contributor was Livingston, which although having very high in migration and hence net migration, also had a much higher than average proportion of out migrants.

The extreme pattern of migration presented by Livingston reflects its high rate of growth since its designation in 1962, with its high rate of turnover possibly reflecting the role of the town within its local region. As the high commuting levels illustrate, a large number of workers travelled either in or out of the town to work, possibly implying high

MIGRATION RATES TABLE 3.8

	IN MIGRANTS		OUT MIGRANTS		NET MIGRATION	
	NUMBER	%POPN 1971	NUMBER	%POPN 1966	NUMBER	%GROWTH 1966-71
NT AVERAGE		23.5		16.3		10.7
LIVINGSTON	900	66.3	68	27.0	832	61.4
EAST KILBRIDE	1172	27.6	682	14.3	1090	17.0
GLENROTHES	1047	38.3	437	23.1	610	22.3
CUMBERNAULD	1289	40.8	291	16.9	998	31.6
IRVINE	736	17.3	252	7.3	484	11.4
SNT AVERAGE	1029	36.1	346	17.7	803	28.7

NT=New Town
SNT=Scottish New Town

Source Champion,Clegg et al (1977)

levels of potential in or out migrants wishing to move nearer to their workplace. Other features, such as the low level of owner occupied housing implying the migration of higher income workers, when promoted, to the surrounding areas, also provide possible reasons for the high levels of migration.

3.9 SUMMARY

Livingston would appear to reflect many features of New Town development in an extreme form. The main reason for this being its high population and employment growth from a small pre-designation base. Also, as has been recognised, Livingston has adapted quickly to its regional setting. Its demographic structure in 1971 showed the most youthful population of all the New Towns, the highest proportion of males and the highest average household size. Though the age structure matured in the seventies towards the Scottish norm the effect was not significant.

The housing stock and the availability of amenities were of a high standard with an extremely high level of publicly rented properties and, although some private developments did occur, an insignificant preportion of private housing. The quality reflecting to some extent the small amount of sub-standard accomodation inherited at designation.

Despite the high growth rate of employment, Livingston did have a very high unemployment rate in the seventies, but when viewed in a regional context the levels do not appear to be so extreme. The structure of the workforce was certainly an extreme of the New Town features with an overrepresentation of skilled manual workers, reflecting the New Town bias towards manufacturing employment. There was also a related deficiency in the level of professional and service employment within the New Town, when compared to the type of employment of residents.

This large discrepancy further illustrates the role and importance of Livingston within its local region and the related importance of both

out and in commuting. Indeed commuting levels involved about 60% of the residents travelling out of the town to work with, in 1977, 35% of these commuting to Edinburgh. The importance of Edinburgh being mainly the provision of professional and service employment which was unavailable in Livingston. Not surprisingly given these levels of commuting Livingston has a high proportion of car owning households (a general New Town feature) with a concentration in the one car owning household group.

The physical development of Livingston reflects the features of the second wave of New Towns where consideration has been given to the increased level of personal mobility created by the higher levels of car ownership and the importance of Livingston within the region. The town's compact linear shape reflects the transport orientated development providing, despite the lack of passenger train service, an extremely efficient transportation network. The road system which precludes through traffic from residential areas minimises traffic flow delays within the town; as its design does not require cross roads, traffic lights or other typical urban bottlenecks. The extensive segregated footpath system, which is unique to British New Towns, complements the public transport service, as an alternative to the car. In addition bus stops have been designed to minimise walk times with most dwellings within 400 yards of the nearest one. These developments are important within the context of minimised work journeys within the town, the majority of employment being located in the peripheral industrial estates.

These features might be considered to typify half of the fundamental choice facing towns and cities, describing towns as they might appear if emphasis was to be placed on the unrestricted use of the car mode, but with emphasis placed on walking to complement the public transport system.

3.10 COMMUTING AND MODE CHOICE

It is clear that commuting is both an important and distinctive feature of the development of Livingston, a form of development which has led

it to represent the divergence between New Towns and the rest of the countries in an extreme way. The integration of Livingston within its regional context is made no clearer than by the levels of commuting in and out of the town, the main constituent of these flows being the large proportion of individuals who commute to work in its neighbour city, Edinburgh.

The journey to work in Edinburgh is of interest not only because of its importance to the New Town, both in terms of its related socioeconomic effects and its planning implications, but also for the novel application it affords the disaggregate models of consumer choice to be employed in this study. In essence the Livingston -Edinburgh commuting journey cannot be typified as either an inter or intra - urban study, being as it is, between a New Town and its big city neighbour at a distance of about 14 miles. It also incorporates the possible effects of New Town characteristics on the choice of mode of individual travellers, both physical and socioeconomic.

In addition the journey to work within Livingston is clearly of importance. The physical development of the New Towns in its transport orientated form as represented by Livingston has presented a number of features which might be expected to influence the choice of mode of the individual traveller.

1. The efficient road transport system which tends to make the car a more efficient mode than in usual urban forms, both as regards time and possibly cost.

2. The attempt to minimise walk times to bus stops, in the light of studies which have shown excess time to be a major deterrent to the choice of mode.

3. The comprehensive system of pedestrian footpaths segregated from major thoroughfares. These provide easier access to bus stops as well as providing an alternative to bus and car for journeys within the town.

4. The higher than average car ownership levels which tend to be the result of a concentration of households owning only one car.

These features will clearly influence both commuting from and within the town, implying that the analysis of these commuting patterns should provide findings which are both novel and indicative of the effects of possible developments within conventional urban settings. Indeed, as we have seen, it is possible to claim that these New Town features typify half the fundamental transport choice facing towns and cities, describing how they might appear if emphasis was placed on the use of the car mode and on walking to complement public transport.

CHAPTER 4

MODELLING TRAVEL CHOICES

4.0 INTRODUCTION

The previous two chapters have been concerned with providing background information on the New Towns and a comparative assessment of Livingston. It is now necessary to consider the available tools of analysis for modelling travelling choices and to provide the theoretical framework for the models to be used in the empirical studies of mode choice.

These tasks are undertaken in this chapter. The first section briefly outlines the arguments for using disaggregate behavioural models, based upon the individual observations. The second section briefly outlines the deterministic theoretical developments which were superceded by the probabilistic choice framework outlined in section three. Section four then considers the structure of transport choices of which mode choice is a part. Finally, section five presents the method of estimation of the logit model to be used in the studies. This section corresponds to the purpose written computer programs used in the study which are presented in Appendices 11 and 12.

4.1 AGGREGATE VS DISAGGREGATE MODELS

Over the years, the realm of travel demand analysis has been dominated by transportation engineers armed with a series of largely ad hoc models. These models have generally attempted to explain and predict aggregate traffic flows between pairs of zones on the basis of aggregate socioeconomic characteristics of the origin and destination zones. Only in the more refined models has there been any consideration of network features. Generally the structure of such conventional models has involved splitting the demand function into the stages of trip generation and attraction, trip distribution, model choice, and route assignment. Each stage being treated separately and calibrated on the basis of observations which are zoned aggregates. There are many expositions of such models and analysis of their weaknesses [1] available in the literature. Thus, it should be adequate merely to outline the common themes.

Conventional models have in most cases been rather simplistic in form, ignoring or inadequately proxying many important variables. Their calibration is mechanical in nature and based upon intuitive derivation generally without regard to any consistent theoretical basis. By nature such models are non-behavioural and non-causal, giving no guidance to the effects on travel decisions of changes in travellers circumstances. Also except for some modal choice functions, an important failing has been the exclusion of the effects of controllable variables and hence a lack of policy orientation. A further important drawback of conventional models relates to their use of data in aggregate form. This can obscure a lot of information contained in the data and averaging over sets of detailed observations can lead to arbitrary definition and subdivision, generating the possibility of false inference. These weaknesses when combined with the non behavioural and non causal nature of the models imply that they cannot be generalised spatially.

1. **See for example: Stopher & Lisco (1970); Hartgen & Tanner (1970); Brand (1972); Domencich & McFadden (1975); DeDonnea (1971); Richards & Ben-Akiva (1975).**

These models have, however, retained prominence in transportation studies mainly because of their simplicity of use, ease of calibration, the wealth of experience in their application, and their successes in various instances. Realisation of their deficiencies, however, has led to a number of developments. Firstly, attempts to increase the internal efficiency and applicability of the models, by giving them a more rigorous theoretical base, studying the determination of important variables, and analysing the interactions between demand, cost and pricing [1]. Secondly, there have been attempts to improve upon aggregate models to make them more responsive to policy variables, by incorporating system characteristics to make them more consistent with economic theories of consumer choice. Such developments, which combine the stages of trip generation, distribution and modal choice are called "direct demand models" [2]. Thirdly, there has been the development of disaggregate models, based upon observations at the level of the individual's travel decisions.

Disaggregate models attempt to overcome the major deficiencies of the conventional models by concentrating the analysis at the level of the individual behavioural unit. This allows the consideration of factors which actually influence the travel behaviour of the individuals and allows more efficient use of available data [3].

1. **See for example: Wilson (1967,1969); Heggie (1969); Evans (1974); Cochrane (1975); Wilson (1967); Moses and Williamson (1963); Sammons and Hall (1977); Goodwin (1973); Mogridge (1967); Meyer, Kain, and Wohl (1966); Fairhurst (1975); Champernowne et al (1976).**

2. **See especially: Papers by Quandt, Wilson, Quandt and Baumol, Mayberry, Quandt and Young in Quandt (1980); and Talvitie (1973).**

3. **Although disaggregate data is used, it is also possible to use information within an individual observation that is at some level of abstraction.**

By investigating the determinants of individual behaviour and seeking causal relationships, such models, apart from providing policy relevant analyses, have the potential of leading to a general theory of travel demand which can be spatially and temporally transferable [1]. Indeed, their consistent theoretical base developed, as shall be seen, from the postulates of consumer rationality and utility maximisation implies such generality.

While it is desirable to estimate the models at a disaggregate level, the use of the models in prediction will generally require some level of aggregation. The transformation of disaggregate models to aggregate prediction models although simple in principle does raise practical problems. However, such problems are equally applicable to aggregate models which have the implicit assumption of homogeneity, within zones and using disaggregate models does allow aggregation to any particular level required by the study. These issues will be considered in detail, in Chapter 8.

The earliest developments in disaggregate behavioural models of travel choice stemmed from the desire to produce more accurate estimates of time elasticities of modal split, often also producing values of time for use in cost-benefit analyses. These developments [2] were mainly of a pragmatic nature with the choice of variables to be used in the models determined mainly by the observation of actual behaviour. The realisation of the necessity for a consistent theoretical base to provide a formal understanding of the nature of travel decisions of individuals and their interactions with other activities led to a number of developments to which we now turn.

1. **Although the evidence for the realisation of this potential in practice is mixed. For example: Watson and Westin (1975) who provide evidence for, and Kirshner and Talvitie (1978) who provide evidence against.**

2. **The pioneering works are Warner (1962); Quarmby (1967); Beesley (1965); Lisco (1967); Lave (1969); Stopher (1968).**

4.2 DETERMINISTIC CHOICE THEORY

The lack of a theoretical base for the early models of transport choice was mainly the result of the inadequacy of conventional microeconomic theory to deal with the specific problems inherent in transport analysis. In particular, the definition of a particular mode and the importance of time in the analysis made the conventional atemporal theory inadequate.

Two developments in consumer theory paved the way for the development of theoretical structures in transport decisions. Firstly, Lancaster's (1966) theory of consumer behaviour, where utility was derived not from the actual goods themselves but from the properties they possessed. This development meant that goods were no longer the direct objects of utility and so consumption could be considered as an activity where goods were the inputs and bundles of characteristics the outputs. Utility, or preferences, ranking the goods only indirectly through the attributes they possessed, both generic and good specific. The traditional approach thus became a special case of Lancaster's more general theory and, as a result, the difficulties of identifying independent sets of travel alternatives was overcome. Alternatives could now be defined by journey attributes such as time, cost, comfort and convenience, known characteristics of the travel modes [1].

Secondly, Becker (1965) developed a model which took explicit account of the allocation of time, introducing time into the individual's utility function. Consumers were considered to combine goods and time to produce activities which constituted arguments in their utility functions. This innovation allowed the handling of the crucial journey attribute, time spent travelling. Becker's contribution represented the point of departure for the introduction of time costs into the choice process and led to models which

1. **Dalvi (1978) presents a model of travel choice based upon the Lancaster framework. See also Hansen (1974).**

provided the theoretical base of a number of studies using disaggregate choice models [1]. It further provided a framework to allow the identification and estimation of values of travel time [2].

The theoretical analyses provided by such deterministic models did not, however, provide a direct correspondence to models which were essentially probabilistic. Though increasing the understanding of the nature of travel decisions empirical results were related to the theoretical base by analogy rather than consistent behavioural backgrounds.

4.3 PROBABILISTIC CHOICE THEORY

The inadequacy of deterministic choice theory in explaining short run travel decisions led to two major developments. Firstly, the belief that consumer's behaviour might have probabilisitc rather than deterministic consistency and that quantal choice analysis, where choice is qualitative rather than quantitative, might be a more apt means of analysis. Secondly, that an alternative "behavioural" basis was required to analyse travel behaviour.

The earliest models of probabilistic travel choice were not based on theoretical statements, rather, broad hypotheses formed the basis for empirical estimation of transport choice models. Simple postulates of human behaviour were expounded in which individuals were considered to choose alternatives on the basis of the levels of service provided by the alternative modes in the transport system, modified by the characteristics of the individual, and their decision making process amenable to modelling using the probabilities of choice.

1. **Developments in the theory of the allocation of time can be traced through Becker (1965); DeDonnea (1971, 1973); Oort (1969); DeSerpa (1971, 1973); Evans (1972).**

2. **For application see for example: Watson (1974); DeDonnea (1971).**

A more formal theoretical basis was provided by the development of psychological choice theory, through the strict utility approach, and an economic choice theoretic framework, through the random utility approach. Both, as shall be seen, leading to similar final model forms.

STRICT UTILITY APPROACH

This approach to the analysis of consumer choice is consistent with the more modern theories of human discrimination and choice. Psychologists consider every decision to be probabilistic (because of minimum variance in discrimination, and dynamic preference changes) but based upon an evaluation of the utilities of each alternative. This can be formalised for travel decisions using the "strict utility" model developed by Luce (1959) based upon his axiom of the independence of irrelevant alternatives (**IIA**) [considered algebraically by Arrow (1963)].

Luce's axiom assumes that the relative odds of an individual choosing an alternative k rather than an alternative j from a given set of alternatives (P_k/P_j) is independent of the presence or absence of a third alternative. Assuming an alternative j provides utility U_j, which is a function of the attributes of the alternative modified by the attributes of the individual, namely,

$$U_j = U(x_j, s)$$

Then the individual is assumed to have an exact measurable utility for each alternative but still to be uncertain of his choice. There is, however, assumed to be a direct correlation between the probabilities of choice and the levels of utility, the higher the level of utility of an alternative the lower the probability of its being chosen. This makes it reasonable to assume that the probabilities can be expressed as a ratio of the utilities, which means the IIA axiom becomes:

$$\frac{P_i(j:A)}{P_i(k:A)} = \frac{P_i(j:B)}{P_i(k:B)} = \frac{U_i(x_j, s_i)}{U_i(x_k, s_i)}$$

where A = the set of alternatives containing only j and k

B = the set of all alternatives

x = the attributes of the alternative

s_i = the characteristics of the individual

Thus, the ratio of the probabilities of choice is determined by the ratio of utilities of the two alternatives under consideration and no others.

It is necessary to define some functional form for the utility function. Without loss of generality, this can be assumed exponential.

$$U(x_j, s_i) = \exp [V(x_j, s_i)]$$

It is also reasonable to assume linearity of V function in the x's as this defines a convex utility curve with diminishing marginal returns for increases in the attributes of the alternatives. Thus

$$\frac{P_i(j:A)}{P_i(k:A)} = \frac{\exp [V(x_j, s_i)]}{\exp [V(x_k, s_i)]}$$

Which for two alternatives gives

$$P_i(j:A) = \frac{\exp [V(x_j, s_i)]}{\exp [V(x_j, s_i)] + \exp [V(x_k, s_i)]}$$

and

$$P_i(k:A) = \frac{\exp [V(x_k, s_i)]}{\exp [V(x_j, s_i)] + \exp [V(x_k, s_i)]}$$

These forms can be simplified, because of the linearity assumption by

by dividing by exp [$V(x_j, s_i)$] or exp [$V(x_k, s_i)$] to give:

$$P_i(j:A) = \frac{\exp\left[V((x_j - x_k), s_i)\right]}{1 + \exp\left[V((x_j - x_k), s_i)\right]}$$

$$P_j(k:A) = \frac{1}{1 + \exp\left[V((x_j - x_k), s_i)\right]}$$

which define the binary logit model of travel choice. This can be generalised to m alternatives giving the multinominal logit model:

$$P_{ij} = \frac{\exp\left[V(x_j, s_i)\right]}{\sum_{\ell=1}^{M} \exp\left[V(x_\ell, s_i)\right]} \qquad \forall \ell = 1, \ldots, M$$

Thus, Luce's IIA axiom, together with more reasonable assumptions of the form of the utility function has led to the specification of a model structure for the analysis of travel choice.

The strict utility approach also gives some insight into the form of probabilistic choice models [Stopher and Meyburg (1976)].

1. The assumption of linearity in the exponent function cannot be extended to the characteristics of the individual since the characteristics would vanish from the

probability definition if this were the case. Thus, socioeconomic variables have to be introduced as alternative specific variables.

2. The linearity assumption clearly implies that differences are the comparative mechanism by which individuals make choices between alternatives.

Use of IIA axioms has both advantages and disadvantages for the model. The advantages are:

1. The same estimated parameters used to determine the choice probabilities in that selection from a subset of alternatives can be used to determine the choice probabilities from the full set. Thus, it is possible to get consistent parameters from data on a limited subset.

2. Forecasts of the demand for new modes can be made using the original estimated parameters, for models containing generic variables (i.e. non alternative specific variables) [Domencich and McFadden (1975)].

3. Through the IIA axiom recursive structures of travel demand decisions can be derived, the separability of the decision structure being compatible with assuming additative separability of the utility function. [Domencich and McFadden (1975)].

The disadvantage of the IIA axiom represents an important problem in the definition of alternatives. This can best be illustrated by example. Consider the choice of mode between car and bus where the probability of an individual choosing the car mode is 2/3. Now supposing a second bus following a different route, but with essentially the same attributes as the original bus mode, is introduced. Intuitively, one would expect that individuals would still choose the car mode with probability 2/3 and choose either of the bus modes with half the probability of the original

bus mode i.e 1/6. The IIA axiom, however, requires the relative odds of choosing the car over either of the bus modes to be 2:1. Hence, the probability of choosing the car would be 1/2 and the probability of choosing each bus mode would be 1/4. This is clearly counter-intuitive as one would expect individuals to lump the two bus modes together, given their similarity rather than to treat them as independent alternatives.

This problem with the IIA axiom, will, however, only be relevant when the "independent alternatives" do not differ significantly from each other, though what constitutes sufficient difference to obviate the problem will be an empirical question. This problem does, however, outline the importance of the definition of alternatives and the care required in making the choice of alternatives for study.

For empirical estimation, it is useful to assume $V(x_j,s_i)$ to be a linear function of the unknown parameters i.e.

$$V(x_j,s_i) = Z^1(x_j,s_i)\beta_1 + \ldots + Z^K(x_j,s_i)\beta_K$$
$$= Z(x_j,s_i)'\beta$$

where $Z^k(x_j, s_i)$ are empirical functions of the x and s variables which have no known parameters. This form is also general enough to allow various forms of the available variables to be used such as complex transformations, and attribute and socioeconomic interaction variables. Further, either generic or non-generic attributes of the alternatives can be incorporated e.g. travel time can be used generally ($Z^k(x_j, s_i)$ as travel time for each alternative, (j = 1,2) or as a mode specific variable ($Z^k(x_\ell, s_i)$ as travel time if $j = \ell$ and zero otherwise). This form of the model is:

$$P_{ij} = \frac{\exp Z(x_j,s_i)'\beta}{\sum_{\ell=1}^{m} \exp Z(x_\ell,s_i)'\beta}$$

RANDOM UTILITY APPROACH

An alternative approach to that outlined is to assume that the individual is a utility maximiser in a deterministic fashion, choosing the alternative that gives the maximum utility [1]. The individual's utility function is assumed, however, to have two components, a representative utility $[V(x_j, s_i)]$ which is the same for all individuals and a random component $[\varepsilon(x_j, s_i)]$ reflecting individual idiosyncracies, unmeasurable components of the alternatives, differing tastes and other unobservable influences. So

$$U(x_j, s_i) = V(x_j, s_i) + \varepsilon(x_j, s_i)$$

Although the individual is a deterministic utility maximiser only the representative part of his utility function can be observed. Thus the analyst has to assign probabilities of choice on this basis. Now

$$P_\ell = \text{Prob}\left\{ U(x_\ell, s_i) > U(x_j, s_i) \right\} \quad \forall j \neq \ell$$

implying

$$P_\ell = \text{Prob}\left\{ V(x_\ell, s_i) + \varepsilon(x'_\ell, s_i) > V(x_j, s_i) + \varepsilon(x'_j, s_i) \right\} \quad \forall j \neq \ell$$

Assuming that the random components are randomly distributed over the population gives the random utility model.

Rearranging the above gives

$$P_\ell = \text{Prob}\left\{ \varepsilon(x'_\ell, s_i) - \varepsilon(x'_j, s_i) < V(x_\ell, s_i) - V(x_j, s_i) \right\} \quad \forall j \neq \ell$$

1. These utilities are essentially indirect utility functions defined as the maximum level of utility obtainable for given prices and income. The alternative set, from which the choice is made, clearly represents the maximising combinations of the characteristics which define the individual alternatives.

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To achieve some form of model structure it is necessary to make some assumption regarding the random components of the utility function:

1. Assume they are independent across the set of alternatives. This implies x_i and x_j must be specific to each mode and thus cannot be common attributes.

2. Make some distributional assumption about random components.

Generally, if we let $\Phi(t_1,.....,t_j)$ denote the cumulative joint density function of the random components and Φ_ℓ denote it's derivative with respect to the ℓ th component then

$$P_\ell = \int_{-\infty}^{+\infty} \Phi_\ell \left[t + V(x_\ell, s_i) - V(x_j, s_i), \ldots, t + V(x_\ell, s_i) - V(x_J, s_i) \right] dt$$

and the specification of any joint probability distribution will give a family of probabilities which depend upon the unknown parameters of the distribution and the function $V(x_j,s_i)$ [Domencich and McFadden (1975)].

For binary choice this reduces to

$$P_1 = \int_{-\infty}^{+\infty} \Phi_1 \left[t,\ t + V(x_1, s_i) - V(x_2, s_i) \right] dt$$

If the cumulative density function of the difference between the random components is denoted as G then

$$P_1 = G[V(x_1, s_i) - V(x_2, s_i)]$$

Figure 4.1 shows that if:

1. The cumulative distribution function of the difference between the random component is

$$G[\ \varepsilon(x_1,s) - \varepsilon(x_2,s)]$$

2. V(x,s) is assumed a linear function of unknown parameters

$$V(x,s) = Z(x,s)'\beta$$

3. The random components are assumed independent of each other and are not dependent on the values of x and s.

Then the specification of the form of G will yield various probability models.

This approach, however, treats the random components asymetrically and is difficult to generalise to multiple choice as a result. Thus, the derivation of the models is investigated for various forms of the distribution of the random components when they are assumed to be independently identically distributed (IID), with the implications for the form of G.

The result is that the arctan, probit and logit models are derived by assuming the components to be distributed Normal, Cauchy and Weibull respectively. However, the only model that provides a readily computationally tractable multiple choice generalisation is the logit [1].

Considering the derivation of the logit in more detail

$$P_i = \int F_i\ [\ \varepsilon^*, \varepsilon^* + V_1 - V_2, \ldots, \varepsilon^* + V_1 - V_J\ ]\ d\varepsilon^*$$

1. **Although recent developments of algorithms have made the probit model computationally more feasible, though still complex and expensive eg Hausman and Wise (1978).**

FIG 4.1

$U(x,s) = V(x,s) + \varepsilon(x,s)$

$P_i = \text{Prob}\left[\varepsilon(x_i,s) - \varepsilon(x_j,s) < V(x_i,s) - V(x_j,s)\right] \quad \forall i \neq j$

$P_i = \int_{-\infty}^{\infty} F_i(t + V_i - V_1, \ldots, V_i - V_J)\, dt$

Specify axioms on selection probabilities namely IIA

BINARY CHOICE

$P_i = \int_{-\infty}^{\infty} F(t, t + V_1 - V_2)\, dt$

$P_i = G(V(x_1,s) - V(x_2,s))$

Assume $V = z_1(x,s)\beta_1 + \ldots + z_K(x,s)\beta_K$

$V = z(x,s)'\beta$

G is CDF of difference between the random components

Assume G independent of x_1, x_2, s

G { negative exponential, positive exponential, uniform

G linear over range of V

$P_i = (z(x_1,s) - z(x_2,s))'\beta$

LINEAR PROBABILITY MODEL

G specified as OGIVE

G Cumulative Normal

$P_i = \phi(\beta z(x_1,s) - \beta z(x_2,s))$

$\phi(V) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{V} e^{-\frac{t^2}{2}}\, dt$

BINARY PROBIT MODEL

G Cauchy

$P_i = \frac{1}{2} + \frac{1}{\pi} \tan^{-1}(\beta z(x_2,s) - \beta z(x_1,s))$

$G(v) = \frac{1}{\pi} \tan^{-1}(v) + \frac{1}{2}$

ARCTAN MODEL

Generalisation to multiple choice difficult because the above assumption treats ε_1 and ε_2 assymetrically

G Logistic

$P_i = \frac{1}{1 + \exp[\beta z(x_2,s) - \beta z(x_1,s)]}$

$G(v) = \frac{1}{1 + e^{-v}}$

BINARY LOGIT MODEL

Now consider ε_1 and ε_2 as IID

$G(v) = \int_{-\infty}^{\infty} F(t)\, F(v+t)\, dt$

ε_1 and ε_2 JOINT NORMAL

$\varepsilon_2 - \varepsilon_1$ NORMAL

PROBIT MODEL

ε_1 and ε_2 CAUCHY

$\varepsilon_2 - \varepsilon_1$ CAUCHY

ARCTAN MODEL

ε_1 and ε_2 WEIBULL

$\varepsilon_2 - \varepsilon_1$ LOGISTIC

LOGIT MODEL

Multiple Choice generalisations computationally intractable or difficult

$\text{Prob}[\varepsilon_i \leq \varepsilon] = e^{-e^{-(\varepsilon + \alpha)}}$

which is WEIBULL

$P_i = \frac{e^{V_i - \alpha_i}}{\sum_j e^{V_j - \alpha_j}}$

CONDITIONAL LOGIT MODEL

then the Weibull distribution

$$\text{Prob}\left[\varepsilon \leq \varepsilon^*\right] = \exp\left(-\exp(-\varepsilon^* + \alpha)\right)$$

Gives

$$P_{\ell} = \int \exp(-\varepsilon^*) \exp\left\{-\exp -\varepsilon^* \sum \exp -\varepsilon^* + V_{\ell i} - V_{ji}\right\} d\varepsilon^*$$

replace exp (- ε *) by t

$$P_{\ell} = \int_0^{\infty} \exp\left\{-t\left(\sum_{j=1}^{J} \exp\left(V'_{\ell i} - V'_{ji}\right)\right)\right\} dt$$

implying

$$P_{\ell i} = \frac{1}{\sum_{j=1}^{J} \exp -\left(V'_{\ell i} - V'_{ji}\right)}$$

$$= \frac{\exp V'_{\ell i}}{\sum_{j=1}^{J} \exp V'_{ji}}$$

In the general case

$$P_{ki} = \frac{e^{V'(x_k, s_i)}}{\sum_{j} e^{V'(x_j, s_i)}}$$

Thus the random utility approach gives the same model as that derived from the strict utility approach.

Stopher and Meyburg (1976) point out that this derivation from the random utility model, gives a new insight in that it provides a specification of an alternative through the random component. The assumption that had to be made to derive the model was that the $_{ki}$ terms be independent across the set of alternatives, which implies that the x components of the random component of the utility function must be unique characteristics of the alternative. This resolves the red bus/blue bus problem encountered in the strict utility model (where the definition of an alternative was left unspecified) on the application of

the IIA axiom. A red and a blue bus could not be considered alternatives as they are unlikely to have distinct ε (x',s) terms.

Clearly, the logit model presented here is based upon non-unique assumptions meaning that there are other possible structural forms for probabilistic choice models. It does, however, have many advantages to support its use. In addition to those presented, it has highly acceptable elasticity properties, as will be seen in Chapter 9. There have been some recent developments of the basic model to overcome the a priori assumption of IIA. Gaudry and Dagenais (1979) and Gaudry (1980) present a modified logit (which they call the "dogit") which is flexible enough to allow choices between pairs of alternatives to be consistent with IIA but simultaneously allows choice among other pairs not to be. However, in this study the IIA assumption presents no problems to the analysis and so the basic logit model will suffice.

4.4 STRUCTURE OF CHOICES

In any analysis of consumer choice some notion of separability of decisions is required to limit the analysis to manageable proportions[1]. Even limiting the analysis to travel related choices still leaves a complex analysis, however, and it is necessary to consider travel choices separately from such related choices as occupation and home location as well as to separate travel choices, such as destination, route and mode choice, from each other. In the last section, such a notion of separability was seen to be inherent in the IIA axiom where the relative odds of choosing one alternative over another were seen to be independent of the existence of any third alternative.

1. **Indeed travel choices are essentially derived demands, travel being an activity undertaken to achieve some end and which may itself be an activity.**

The first consideration in separating travel is usually to relate them to a time scale. In this way such decisions as employment location, residential location and housing type can be considered as long run decisions; automobile ownership and commuting mode choice as medium run; non-work trip travel decisions, including frequency destination and mode choice, as short run [1]. Now the short and medium run decisions can be analysed, conditional on the long run decisions i.e. the long run decisions can be taken as given.

In this study the analysis is of mode choice for the journey to work, which is a medium term decision. Thus, the analysis is undertaken assuming the long run ones as given. In focusing on the work journey the analysis is simplified by the destination, origin, frequency, time of day and, as a result of habit , route choices being fixed. The treatment of car ownership and its relation to mode choice is considered in Chapter 6 and so will not be dealt with here. It is, however, worthwhile considering the structures of choices of use in the analysis of the related travel decisions.

There are essentially three categories of model structures for the complex choice situations involved in travel analysis. It is important to note that these structures do have limited behavioural implications, although simply because it is analytically convenient to define sequential models does not necessarily require the assumption that the individuals actually make sequential decisions [2].

The simplest structure is that of independence, that is assuming that all of the choices are mutually independent of each other. Thus, if, for example, mode and destination choice are considered, P_M being the probability of choosing a particular mode and P_D the probability of choosing a particular destination, then the joint probability P_{MD} will simply be the product of the individual probabilities.

1. See Ben-Akiva and Atherton (1977).

2. Stopher and Meyburg (1976)

$$P_{DM} = P_D \times P_M$$

Alternatively, one could postulate a recursive structure where one of the decisions was made and then the others made conditional upon the first. Thus, if the destination choice is followed by the mode choice

$$P_{DM} = P_{M/D} \times P_D$$

where $P_{M/D}$ is the probability of choosing a particular mode conditional on the choice of a particular destination [1]. Finally, it is possible to consider a simultaneous structure where the choice of mode is dependent on the choice of destination and vice versa [2].

The assumption of independence clearly has unacceptable implications for travel demand models as the various choices are evidently not mutually exclusive. A recursive structure will be more acceptable, especially, regarding the analytical convenience of the structure. It does however, require an assumed sequence and hence, some sensitivity analysis of that sequence. A simultaneous structure is probably the optimal structure but often provides an extremely complex model in practice, which can lead to the necessity to consider the simpler recursive structure.

4.5 ESTIMATION WITH DISCRETE DEPENDENT VARIABLES

The standard OLS regression model is:

$$y_i = x_i'\beta + \varepsilon_i \qquad i = 1, \ldots, N$$

$$\varepsilon_i = \text{error} \begin{cases} E(\varepsilon_i) = 0 \\ \text{Var}(\varepsilon_i) = \sigma^2 \\ E(\varepsilon_j, \varepsilon_k) = 0 \quad j \neq k \end{cases}$$

where $x_i'\beta = \sum_k \beta_k x_{ki}$

1. **This would usually incorporate some feedback effect in the utility function of the mode choice. See for example: Domencich and McFadden (1975).**

2. **See Stopher and Meyburg (1976); Richards and Ben-Akiva (1975). Also see Ben-Akiva (1975), Liou and Talvitie (1975) and discussants in the same publication for the debate on recursive versus simultaneous structures.**

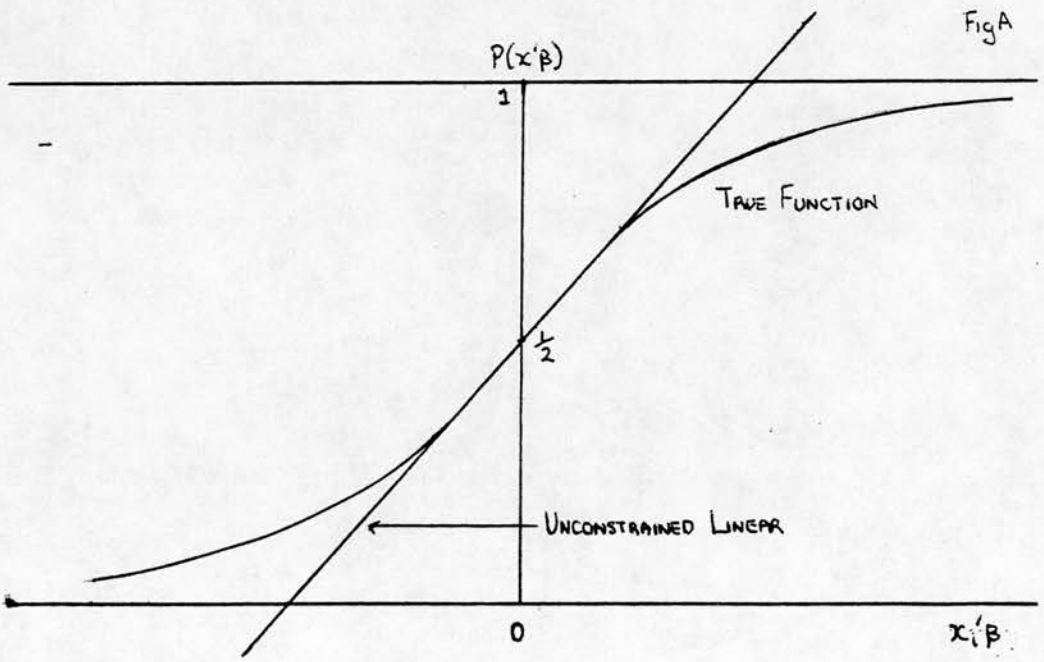
In attempting to apply this to the situation where dependent variable (y_i) is dichotomous

$$y_i = 1 \text{ if event occurs}$$
$$= 0 \text{ otherwise}$$

the conditional expectation of the y_i given the values of the k_i's can be interpreted on the conditional probability of the occurrence of an event i.e.

$$E(y_i/x_i) = x_i'\beta = P(y=1/x'_i\beta) \quad i = 1,\ldots,N$$

If we consider that the larger the values of $x'_i\beta$ the greater will be the chance that y = 1 (i.e. the event will occur) then we could consider a monotone relation existing between the probability of y_i being equal to 1 ($P(y_i = 1)$) and the value of $x_i'\beta$. Now the true probability function must lie between zero and 1 and be non decreasing. Then it will have a characteristic S shape (sigmoid) of a cumulative distribution function:



Though a straight line can be used to approximate the function in its middle range it will be a poor approximation at very low and very high values of $x_i'\beta$ violating the 0-1 limits.

A better approximation can be achieved by constraining the straight line by breaking it at the extreme values and so causing it to move along the assymptotes. To fit such a line, however, it is very difficult and further, in estimation the solution will be non unique and the estimation procedure very difficult. [Nerlove and Press (1973)].

These difficulties led to attempts to use linear regression with the binary y_i as the dependent variable . This, however, has a number of important problems - Watson (1974):

1. HETEROSKEDASTICITY

The discrete form of the variable leads to restrictions on the values taken by the error term. From (1)

$$\varepsilon_i = y_i - x'_i\beta$$

then given

$$y_i = \begin{cases} 1 & \varepsilon_i \text{ must be } \begin{cases} 1 - x'_i\beta \\ - x'_i\beta \end{cases} \\ 0 \end{cases}$$

and hence ε_i can only take two values.

Now the variance is

$$\text{Var}(y_i/x_i) = \text{var}(\varepsilon_i) = x_i'\beta(1-x'_i\beta)$$

and being dependent on the values of the x_i's, not constant. Thus, the homoskedastic assumption of least squares is violated meaning that least squares will generate inefficient estimators and lack precision in predictions. Further, using generalised least squares will not provide a satisfactory solution to this problem.

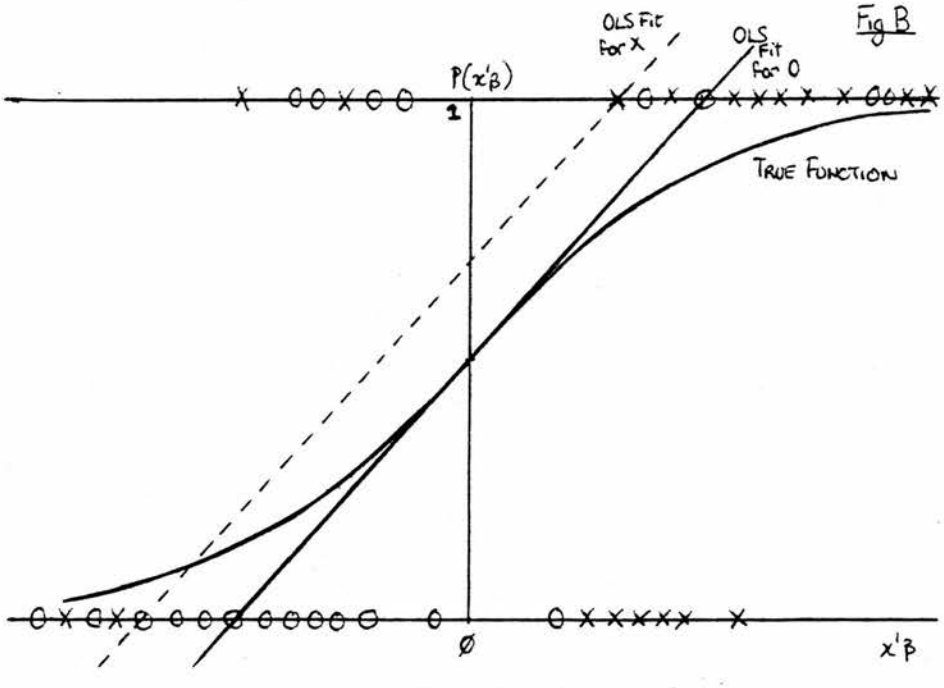
2. DISTRIBUTION OF THE ERROR TERM

As has been shown, the distriubtion of the error term (ε_i) will not be normal because of the discrete dependent variable. Thus, the distribution of the coefficients will not be normal and the

traditional tests of significance on the coefficient estimates will not be applicable. This means that the multiple R^2 will not be meaningful and the estimated standard errors will be inconsistent.

3. UNCONSTRAINED

The linear combination $x_i\beta$ can take any value on the real line while y_i and hence $E(y_i \mid x_i)$ must lie between 0 and 1. Thus predictions outside the 0 - 1 interval may be produced for small or large $x'_i\beta$ values, and as shown in Figure B , the fitted linear relationship will be exceptionally sensitive to the location of the explanatory variables, Nerlove and Press (1973):



Further, as the y_i's are not normally distributed, there will not be a linear method of estimation which will be fully efficient, [Cox (1970)]. Thus the least squares estimator can always be improved upon, even if it is corrected for such faults as heteroskedasticity, because it is still linear.

It would appear justified, after the previous discussion to consider more appropriate methods of estimation. Two approaches based upon the dichotomous dependent variable with the range of $E(y_i/x_i)$ restricted to the unit interval are logit and probit. The probit approach will now be outlined and then the logit approach considered in more detail.

PROBIT ANALYSIS

This approach is based on the idea that if members of a population are subjected to varying levels of stimuli, that can vary over an infinite range, the frequencies of responses will be distributed normally, Finney (1971). The responses are of the occur/not occur dichotomous variety and the cumulative distribution of these responses by their level of stimuli will give the normal sigmoid curve already outlined.

$$\text{Thus if} \quad y_i = 1 \text{ if event occurs}$$
$$= 0 \text{ otherwise}$$

$$\text{then} \quad P_i(y_i = 1) = F(x'_i\beta) \quad i = 1,\ldots,N$$

Probit analysis estimates this relation, where $F(t)$ is taken to be the cumulative density function of the standardised normal distribution

$$P_i(y_i = 1) = \frac{1}{2\pi}\int_{-\infty}^{N} e^{-\frac{1}{2}(x_i'\beta)^2} \qquad i = 1,\ldots,N$$

which can be solved using the maximum likelihood estimation (MLE) approach.

LOGIT ANALYSIS

This approach is basically the same as probit. A transformation of the probabilities of an event occurring, $P(y = 1)$, is sought that can take the value of the explanatory variables from $-\infty$ to $+\infty$ while restricting the probability itself to the 0 - 1 range.

Thus again

$$P_i(y_i = 1) = F(x'_i \beta)$$

but in this approach the cumulative density function $F(t)$ is assumed to be that of the logistic distribution, namely,

$$F(t) = \frac{1}{1 + e^{-t}} \qquad -\infty < t < \infty$$

which gives

$$P_i(y_i = 1) = \frac{1}{1 + e^{-x_i'\beta}} = \frac{e^{x_i'\beta}}{1 + e^{x_i'\beta}}$$

which can be written

$$x_i'\beta = \log\left[\frac{P_i(y_i = 1)}{1 - P_i(y_i = 1)}\right]$$

This again can be solved by ML estimation technique.

The logit transformation can be justified by recourse to the fact that it is _simple and tractable, algebraically and computationally. Its cumulative density function is also numerically close to the normal CDF while the probit model is less simple to work with.

MAXIMUM LIKELIHOOD ESTIMATION

In estimating a relation using the maximum likelihood method one is attempting to maximise the chance (likelihood) that the population implied by a specific relation, would give rise to the sample that is observed.

Thus the ML technique speculates on various possible populations, considers the possibility that they would imply the observed sample and chooses the population which maximises this possibility (likelihood). In the case of regression, for example, the regression line would be tested

with different coefficient values, finding the likelihood at each stage and stopping when this likelihood is maximised. The likelihood at each stage being the joint probability density of the error terms for the observed sample.

Hence the likelihood function to be maximised will, for

$$P_i(y_i = 1) = F(x'_i\beta)$$

be

$$L(y_i \mid x_i) = \prod_{i=1}^{N} [F(x_i'\beta)]^{y_i} [1 - F(x_i'\beta)]^{1-y_i}$$

To find the ML estimates of the population parameters, the simplification of maximising the log of the likelihood is used.

$$L^* = \log L = \sum_{i=1}^{N} \log[F(x_i'\beta)]\, y_i + \sum_{i=1}^{N} [\log(1 - F(x_i'\beta))](1-y_i)$$

In the case of the logit

$$L = \prod_{i=1}^{N} P_i^{y_i} (1-P_i)^{1-y_i}$$

$$L^* = \sum_{i=1}^{N} [\log(P_i)]y_i + \sum_{i=1}^{N} [\log(1-P_i)](1-y_i)$$

where

$$P_i = \frac{1}{1 + e^{-x'_i\beta}} = \frac{e^{x_i'\beta}}{1 + e^{x_i'\beta}}$$

This ML procedure can be carried out by means of an iterative process such as the Newton Raphson method used in this study [1]. McFadden (1973) has shown the estimates to be unique whenever it exists, and

1 See Appendix 8

proved it to be virtually certain to exist in samples of more than twenty observations.

GOODNESS OF FIT

Conventional goodness of fit measures as used in linear regression analyses are not applicable to the logit, except for "t" tests on the individual coefficients. Although the relevant measures are considered in Apprendix 4, it is worthwhile to briefly outline those presented in the tables showing the estimation results in the studies. Firstly, "t" tests on individual coefficients are relevant and are presented in brackets, below the coefficient estimates. Secondly, a number of measures which test the models as a whole are presented. These are based upon the likelihood ratio which tests the null hypothesis that the dependent variable is independent of the value of the explanatory variables. Considering the likelihood ratio:

$$\lambda = \frac{L(\hat{\beta}_0)}{L(\hat{\beta}_0, \cdots, \hat{\beta}_k)}$$

where $L(\hat{\beta}_0)$ is the value of the likelihood function evaluated at the null hypothesis and $L(\hat{\beta}_0, \ldots, \hat{\beta}_k)$ is the value for the estimated model then $-2 \log \lambda$, the log likelihood ratio (LLR) is distributed X^2 with k-1 degrees of freedom.

The other reported goodness of fit statistics are then analogies of the R^2 statistic in linear regressions:

PSQ - rho squared $$\rho_1^2 = 1 - \frac{L^*(\hat{\beta}_0, \ldots, \hat{\beta}_k)}{L^*(\hat{\beta}_0)}$$

where L* is the log of the likelihood

LLI - log likelihood index = $$\left[\frac{k+1}{k}\right] \cdot \left[\frac{\rho_1^2}{1-\rho_1^2}\right]$$

which is distributed $F_{k,k+1}$

APSQ - ρ^2 adjusted for degrees of freedom

$$= 1 - \frac{L^*(\hat{\beta}_0, \ldots, \hat{\beta}_K) / K}{L^*(\hat{\beta}_0) / N - K + 1}$$

PSEUDO RSQ - a variant on rho squared

$$= 1 - \exp \left\{ -2 \left[L(\hat{\beta}_0, \ldots, \hat{\beta}_K) - L(\hat{\beta}_0) \right] / N \right\}$$

It is important to note that, although ρ^2 will be between 1 and 0, a perfect fit would give a value of about 0.7 and a value between 0.2 and 0.4 can be considered to imply a good fit.

CHAPTER 5
THE JOURNEY TO WORK IN EDINBURGH: FORMS OF LEVEL OF SERVICE VARIABLES

5.0 INTRODUCTION

Having developed the theoretical model for the study, it is necessary to consider the practical limitations imposed by the actual form of the study. This involves both developing practical forms from the theoretical constructs, such as deciding on the form in which the variables should enter the model, and taking into account the practical limitations imposed by the available data. These tasks are undertaken in the next two chapters, and a model of the determinants of mode choice for the journey to work between Edinburgh and Livingston is developed.

As shall be seen, there are a number of practical constraints imposed by the available data, however, where possible attempts are made to give tentative interpretations of the implications for the analysis. The estimations are made using three samples - the total sample; the car available sample which comprises those individuals who have at least one car, and the heads sample which contains only those individuals who were heads of their household. The use of these samples allows the comparison of the behaviour of the variables over different samples, but also, as shall be seen, is important in considering the problem of car ownership, and identifying distinct sub-groups within the total sample.

This chapter presents the general problems of applying the disaggregate models. The first three sections outlining the general practical problems inherent in deciding on the form of the level of service variables. Thus, whether times and cost should be the values reported by the individuals or, those measured by the analyst; whether travel time should be decomposed into components of in- vehicle and out of vehicle time; what mathematical form the level of service variables should take, are considered. The fourth section gives information on the source and form of the data followed by the convention adopted in

creating the engineered time and cost values for the study. On the basis of the previous sections, section 7 presents the time and cost variables which are available for the study and section 8 reports the empirical results of their performance. Section 9 then concludes the assessment which argues in favour of the difference form of the level of service variables.

5.1 PERCEIVED vs ENGINEERED DATA

Introducing level of service variables into the model requires considering whether reported values (as answered in the questionnaire) or measured values (engineered, as evaluated by the researcher) of the variables are relevant in the analysis.

Reported values represented responses of individuals to survey questions and as such are representative of the value as perceived by the individual, and this can clearly differ from the true value. A typical traveller will not be able to measure the exact times and costs for a given trip. Apart from the reported value being based on memory, the traveller has no reason to precisely measure the time taken for trips and would have difficulty in allocating the costs of the trip, especially if concerned with car costs or seasons tickets. Also individuals tend to have difficulty in distinguishing small units of time and usually round to, for example, five minute intervals. Further, when an individual considers the alternative mode of travel to that chosen, a distinct anti-modal bias will often be shown, with the non-chosen mode being seen as worse than it is or the individual's choice of mode being rationalised to make it seem more reasonable. It is also possible that in circumstances where an interviewer is involved, the individuals will give the response that they feel is expected, which can be influenced by the approach, personality or personal characteristics of the interviewer.

Measured or engineered values, are those values the researcher measures objectively. Although these pertain to the real values there will be measurement errors involved, which can cause bias. The real travel times and costs for a trip could, in theory, be measured

accurately by the researcher actually following and observing the individuals on their journey, taking into account each aspect of time and cost involved. In reality, however, practical limitations, mean that engineered values are based upon bus schedules, average car speeds and costs, zonal times and other standardised data. Such data, based as it is upon a set of conventions, will in general correspond to the values which are registered on average and not necessarily to the average value for the particular trip under study.

The use of reported data can be justified by arguing that the model (in this case of mode choice) attempts to find a relation between the choice made by the individual and the stimuli experienced and, hence, that those values perceived by the individual are the relevant ones. If perceived values are not used then the individual's choice decision is being modelled on the basis of information that is not known to that individual.

In contrast, it can be argued that the "perception process", or the behavioural base of the decision making process, is subsumed by the adequacy of models which assume people behave "as if" their choices were based on the measured data (taken as an estimate of the actual values). This approach has the added advantage of reducing the data collection required, and has been shown to give a high degree of predictive accuracy [1]. Further, it is possible to argue that, even if the individual choice is based on perceived data, in the case of frequent journeys, such as the work journey, a learning process is involved which causes perceived values to converge towards actual values as the journey is continually experienced. Hence, for such journeys there should be little difference between perceived and measured values.

1. **This is relevant to the Neo-Classical consumer theory where consumers are assumed to act as if they maximise utility, have perfect knowledge, etc...The outcome of which is the creation of falsifiable hypotheses.**

One of the most important tasks in the context of mode choice modelling is prediction. Whether temporal or spatial, this requires the input of new level of service data pertaining to the new situation although retaining the structural parameters. The confidence in such predictions will be influenced by the spatial, or temporal constancy of the relationship and the comparability of the data used in calibrating the original model and that used for prediction. As a result, the use of perceived data for prediction will be inadequate as so little is known of the relation between perceived and actual data that it would not be possible to measure perceived values for the new situation. Further, for the same reasons, it is not possible to estimate how perception may change over time (or space) as a result of changes in the environment or circumstances.

In practice, as has been noted, reported values which are used to represent perceived values are not necessarily exact measures of the individual perceptions, and will usually be biased. Thus, although the optimal strategy might be to find the relation between perceived and reported values, when the model is to be used for predictive purposes, the non-feasibility of such a task makes the use of measured data necessary.

In this study, the use of reported data is precluded, as shall be seen by practical reasons of non-availability of information for non-chosen alternatives and the unsuitability of the available data. Thus, as often occurs in practical applications, the dilemma of choosing the relevant values does not arise.

5.2 EXCESS TRAVEL TIME

In considering the time taken for a particular trip by a particular mode, the time spent actually travelling on the mode, the in-vehicle travel time, can be distinguished from the time spent outside the mode, such as walking or waiting. It seems reasonable to suggest that these two aspects of travel time might be weighted differently, in the sense of giving different levels of (dis)utility per unit of time. Further, one

would expect that the excess time spent walking and waiting, would be considered more onerous by the travellers because of the inherent effort required and/or discomfort undergone.

Empirical studies of travel choices have generally made this distinction, with door to door travel time being broken upon into in-vehicle and out of vehicle (excess) travel time; out of vehicle time often being further disaggregated into walking and waiting time. Quarmby (1967) was the first to make such a distinction between in-vehicle and excess time and many other studies have since tried to improve the specification of models by the disaggregation of travel time into its various components. The results of most of the studies was to give support to the hypothesis of differential weighting of the components of travel time with high coefficient values being found for excess time or its components.

These findings seem reasonable intuitively as one of the main advantages of the car mode over the bus is the lack of walking and waiting time implied. Although it might be possible to argue that these advantages could be offset by walking distance from car parks, congestion and the use of bus lanes and soon, it is nevertheless, reasonable to expect the importance of excess time in determining the choice of car.

There are problems involved in the disaggregation of travel time, however, mainly concerned with the data used, Clearly excess time, although heavily weighted, tends to be rather inaccurately reported and can be very difficult to engineer. This will be especially true of wait times, where for precision it might be considered necessary to have regard for service delays, rather than just the commonly used random arrival. Indeed, one might argue it is wait time caused by service delays that is most important, especially if people know the scheduling of services. In addition, it is extremely difficult to get reported values or to engineer excess travel times of non-chosen alternatives.

Such problems imply that the actual results gained from using excess time variables might be somewhat inaccurate, or misleading. Further,

if models estimated with such variables are used in prediction or forecasting, the data for excess time variables becomes far more difficult to estimate. Thus, there are many practical reasons for the lack of inclusion of level of service variables of the excess time form.

5.3 MATHEMATICAL FORMS OF LEVEL OF SERVICE VARIABLES

Though useful insights are given in the theoretical development of the model as to the form in which the travel times and costs (alternative characteristics) should enter the model, there is still scope for empirical investigation. A number of forms have been used in previous research, namely difference, ratio, log of ratios and relative difference.

The difference form implies that the choice decision is based upon the absolute difference between the time and cost characteristics of the alternative modes. This implies that if the total travel time for a journey increases then the weight given to a particular time saving (or the effect on the level of utility) will remain constant. It has also been seen that this form can be shown to be implied by the derivation of the logit model.

A ratio form for the time and cost variables implies that the choice decision is based upon the relative differences of the time and cost variables between the alternative modes. This clearly diminishes the effects of absolute differences and will weight a given travel time or cost saving less as the total travel time or cost increases. Thus, the longer a journey, for example, the less the utility attached to a particular time saving.

When the cost and time variables are entered as the log of the ratios the choice is considered to be based upon the log of the relative differences between the characteristics of the alternatives, or the absolute difference between the logs of the characteristics of each alternative. That is:

$$LRT = \log (CT/BT)$$
$$= \log CT - \log BT$$

The relative difference formulation relates to the differences between the time and cost of the alternatives divided by the average of the times or costs of the alternatives. That is for time:

$$RDT = CT - BT/ \tfrac{1}{2} (CT + BT)$$

This implies that the choice is based upon the difference between the time or cost characteristics of the alternatives relative to the total time or costs (the average of the times or costs being used because it is not clear whether the individual's evaluation would be relative to the slowest or fastest mode, for e.g.). Thus, the longer or more expensive a journey, the less effect a given absolute difference between the modes will have on choice. (That is, the lower the level of utility attached to a particular time or cost saving will be).

Quarmby (1967) considered the possibility of using the ratio, difference and log of ratio forms in the study of mode choice. He compared their relative strengths and weaknesses of performance in predicting behaviour. The same forms were further studied by Stopher and Lavender (1972) with similar conclusions. The ratios were found to be inferior and the log of ratio form differed little, as might be expected from the fact that the log of ratios can be expressed as the difference between the logs.

$$\log(CT/BT) = \log CT - \log BT$$

Watson (1974) found that the relative difference form of the time and cost variables was superior to the difference in his inter-urban application. This results had plausibility in the context ofthis particular empirical study as it might be expected that the absolute value of the time and cost differences would be less important for the longer time, distance and higher cost outlays involved in inter-city trips. Watson didn't, however, consider whether the range of times and costs implied this.

In the derivation of the binary logit model, it was seen that the level of service difference form could be implied, as the way in which the variables should enter the model. Furthermore, in this study the range of travel time and cost differences is small (because of the nature of the commuting journey, its uniformity) making the assumption of constant utility of time and cost savings, as the total time or costs increase appear plausible.

Thus, although the Edinburgh-Livingston journey to work cannot be readily categorised as inter-city or intra-urban, pride of place shall be given to the difference form of the level of service variables. The alternative forms considered will be investigated empirically and compared to differences, but will only be considered further if they prove markedly superior.

5.4 SURVEY DATA

Livingston Development Corporation's Employment and Travel Survey was carried out in late January 1975 and involved 100% coverage of the private residential areas, Murieston and Woodlands Park, and 20% of the remainder of the town, one in five of all households being selected on a random basis. This gave a total sample of 840 households.

The main purpose of the survey was to provide information on the residents' travel to work, to the shops and for recreation, together with car ownership levels to aid in the planning of roads and the provision of public transport [1]. In addition, information was gathered to aid the proposal of a passenger railway link with Edinburgh and Glasgow. However, as the survey was carried out in conjunction with Lothian Regional Council, the emphasis was on travel to Edinburgh.

For this study of the journey to work in Edinburgh, the relevant subsample of the observations was selected. It was found that 221 households had one or more members employed in Edinburgh [2]. This

1. **See Appendix 1 for Questionnaire.**
2. **For a comparison of the features of this sample with the total sample, see Appendix .**

subsample was broken down into the individual observations, retaining information on both household and individual characteristics and isolating the individuals who reported that they worked in Edinburgh. As some cases contained more than one response for such variables as mode choice and reported journey time, it was necessary to use judgement to decide on the main mode of travel and to provide consistency between the mode chosen and the time reported.

The result was a sample of 249 individuals who commuted to Edinburgh. This was, however, reduced of necessity by dropping observations for which no address was specified, leaving a sample of 231. This was further reduced to a final sample of 219 by dropping the observations where the reported mode of travel was other than car or bus. The reason for this being the estimation problems for times and costs for modes other than car or bus, and the undoubted dominance of these modes for the journey to work in Edinburgh.

When a further subsample, including only those individuals who had a car available was taken, using the criteria of the individual's household having only one or more cars, the resulting number of observations was 179. The creation of a subsample which contained only those individuals who were the head of their household gave a sample of 143 observations.

5.5 EMPIRICAL DERIVATION OF LEVEL OF SERVICE VARIABLES+ TRAVEL TIME

Reported door to door travel times for both the journey to and from work were available for the mode chosen. However, no information was available for the non-chosen alternative mode, indeed, the available relevant alternatives were not even stated. As the study is concerned with the probability of choosing car for the journey to work, and car and bus are clearly the dominant modes, it was assumed that bus was the alternative when car was chosen and vice-versa. The engineered travel time and cost values were thus estimated on this basis.

Although both legs of the work journey had travel times reported for them, they were found to be predominantly the same and hence for simplicity it was decided only to consider the journey to work, assuming similarity of the return journey.

To engineer the in-vehicle travel time for bus journeys from the districts in Livingston to those in Edinburgh, bus timetables were used, the relevant time being that of the fastest service. Where transfers were necessary within Edinburgh the journey time was estimated from the relevant city services' timetables, using judgement, on the basis of minimum time (or distance) as to the route chosen. Unless the destinations where en route the travellers were assumed to travel to the West End (for Morningside and Granton), or to the East End (St. Andrew's bus station) and then to transfer.

In considering out of vehicle travel time for the bus journey problems were caused by the lack of knowledge of the exact destination of commuters. Only rather wide destination zones were available, and so it was not possible to estimate walk and transfer times within Edinburgh. It is, however, possible argue that wait and transfer times within the city are minimal because of high bus frequency, though the lack of any estimates of walk times is certainly important.

Within Livingston, the exact address of each individual was known and so estimates of walk times could be made. For most districts, the position of bus stops were designed such that dwellings were within 400 metres of a bus stop. This clearly diminishes the importance of walk time and gives credibility to the simple district averages used.

A walk speed of 3.4 mph was assumed, with all areas except Murieston (1 mile) having 200 metres average walking distance. However, for Deans, Knightsbridge and Ladywell, faster services were available at the edge of the district and hence, at the expense of increased walking distance, so 400 metres average distance was used.

For wait times within Livingston, the frequencies of the buses were estimated from routes and timetables for each district, assuming random arrival, one half of the headway for waiting times if under 7 minutes. The reasoning behind this valuation was that individuals would get to know schedules if services frequencies implied a headway of more than 14 minutes (a 7 minute wait) and as there would be no random arrival after that ceiling was reached [1]. The importance of wait time is, however, questionable as, with the limited frequency of buses within Livingston, it might be expected that individuals would get to know schedules (especially for the frequent work journey) and hence, would minimise wait times rather than arrive randomly (as in a city with frequent buses). Thus, wait time might be considered to be only that attributable to service unreliability for which, not surprisingly, there is no available measure.

It can be argued that using excess travel times within Livingston implies a problem of spurious accuracy as the lack of estimates of such for the trip destinations detracts from the usefulness of those at the origin. Indeed, it might be argued that the destination excess times are the most important.

Car travel times were estimated on the basis of a travel time matrix supplied by Lothian Regional Transport Highways Department. It was necessary to use representative zones for the coded destination zones, as reported in the survey data, because of differences in precision and to take account of distances from zone centroids at the origin [2]. As regards excess time for the car journey, it was assumed that there would be no walk or wait time within Livingston as cars could be parked

1. **This is a generally used criteria and is employed by Lothian Regional Council in transport studies.**

2. **The trip matrix was more detailed, as regards zoning, for within Edinburgh than for the Lothian region. The coded data was, however, far more detailed for within Livingston, where individual addresses were known, than for Edinburgh, where only wide destination zones had been used.**

or garaged close to dwellings. For within the city time from parking place to work was reported for car users but no information was available for when car was the alternative, nor could this be estimated. Hence, it was simply assumed that car excess time was zero.

As result of these considerations, it was only possible to estimate transit walk and wait times for within Livingston, and it was not possible to do other than assume car excess time to be zero, which is anyway a common assumption. Thus, the main variables of concern were constrained to be in-vehicle travel time or reported door to door travel time [1] though attempts will be made to rectify this deficiency by using the origin excess time estimates only, and dummy variables reflecting whether transfers were necessary, or would be necessary for the bus trip.

5.6 EMPIRICAL DERIVATIONS OF LEVEL OF SERVICE VARIABLES: TRAVEL COSTS

The only reported travel costs available in the survey was the cost of the car journey between Livingston and Edinburgh and the cost of parking for those who travelled by car. There were neither reported costs for bus users nor reported costs for the alternative mode, and so it was necessary to estimate them.

Bus costs to Edinburgh were specified in a section of the questionnaire designed to elicit the potential patronage of a proposed rail link. These were £2.70 for a five day weekly return which gave a single trip cost of £0.27 one way. It was this figure that was used in the study after adjustments were made for the cost of travel within Edinburgh, when transfers were required, as computed from the relevant fare structures.

1. **Engineered or measured data pertain to estimates of in-vehicle travel time while the reported data relate to door to door travel time. Note however, the problems of using reported data because of the coding used.**

Engineering car costs required measuring the distance between the address origin [1] in Livingston and the destination zone in Edinburgh, based upon the same representative zones utilised in the travel time estimation. There were two available approach routes to Edinburgh, one from the North, via Corstorphire, and one from the South, via Sighthill (see Fig. 1). The relevant route was that judged to be optimal when the individual's origin and destination were considered.

Having estimated trip distances car costs were computed using the distance multiplied by the cost per mile for the average family car, as details were not available on the type of car. The figures for car costs, in 1975, were obtained from the A.A. with the 1001 to 1500 cc range of car being considered representative of the average family car. The evaluation was based on 10,000 miles and petrol was evaluated at £0.73 per gallon. Three compositions of cost per mile were considered:

1. The marginal running cost considering only petrol and oil or what might be considered out of pocket costs. Various studies (e.g. Quarmby (1967) have used this evaluation arguing that it is only these out of pocket costs that are perceived by the car user when undertaking a journey.

2. The running costs considering all variable costs including petrol, oil, tyres, servicing, and replacement.

3. The total costs, including running costs and standing charges, ie., including fixed costs.

1. **Although the measurements were made from zone centroids, the zones were made small enough to make the distance between the centroid and the specific dwelling insignificant. Such approximation is of little importance given the imprecision of the destination zoning.**

The figure for 2 and 3 can be considered to represent the average variable costs and average total costs of car use. These valuations are considered because of the uncertainity of how drivers allocate or perceive car costs. It is possible to argue (Lave [1969]) that if the car is purchased especially for the work journey then average costs are important, either average variable or average total, depending on the rationality of the individual. If, however, the car is owned for other reasons, then it is the marginal out of pocket costs that are important. It would seem plausible to suggest that the latter would generally be the most useful. The average costs will, however, be used empirically and compared with the model using marginal costs to see if such an approach is acceptible. It is usually assumed in such studies [Stopher and Meyburg (1976)] that drivers do not have any more than a very limited awareness of the true cost of running a car [1].

Although desirable, it was not possible to give consideration to various other relevant factors that can influence car costs such as type of car of speed of travel because of lack of information. Further, although reported parking costs were available for car users, it was not possible to estimate them for individuals where car was the non-chosen alternative and so not possible to use them in the model.

In atttempting to use reported travel time values, problems were caused by the rather wide coding catergories used in the data. For compatibility with the engineereed data, which was required to compute the values for the non-chosen alternative, it was necessary to use the median of the categories:

Time (Mins)	Median
<than 10	5
11-20	15
21-40	30
41-60	50
61-90	70
91+	100

1. **Generally for commuting trips, the best average costs have proved to be out of pocket costs.**

Using these median values clearly has the effect of limiting the spread of the observations which means the resulting variable is likely to behave poorly in empirical estimation, Hensher and Hotchkiss (1975) encountered this problem. Although using engineered continuous values, they found a poor spread of observations and cited this as the cause of the travel time difference varible in their model, taking the incorrect sign.

As shall be seen, the same result was encountered in this study with the semi-engineered variables (using reported values for the chosen mode and engineered for the non-chosen alternative) behaving badly. A further attempt to achieve compatibility by coding the engineered travel times, as estimated for the non-chosen alternative, and using the median in the same way for the reported data, was singularly unsuccessful.

The considerations, together with the arguments already put forward in favour of using measured data, seem to imply that it will be necessary to use the engineered forms. As shall be seen, further support for this conclusion is provided by empirical estimation and evaluation.

5.7 AVAILABLE TIME AND COST VARIABLES

After consideration of the available information both reported and engineered, the following time and cost variables were created:

TIME

CT - car time as measured and hence in the form of in-vehicle travel time

CTT - car time as semi-engineered, using reported travel time (the medians of the coding categories) when car was the chosen mode and engineered values when car was the non-chosen mode. Although this seems to imply inconsistency as the reported time is door to door travel time, while the engineered relates to in-vehicle travel time, the lack of

available information on car excess time makes an assumption of zero excess time for car journey necessary.

CTT 1 - car time semi-engineered. A variation of CTT where the reported travel time to work had the median of the categories of reported time from parking place to work subtracted from it, with engineered values used when car was the non-chosen alternative. This was an attempt to make both engineered and reported values relate to in-vehicle travel time in case CTT with its assumption of zero excess time proved inadequate.

BT - bus travel time as engineered hence relating to in-vehicle travel time.

BT1 - bus travel time with estimated walk time within Livingston added to it. This was an attempt to include origin excess time within the variable where wait time is assumed zero, although the non-availability of destination excess time makes this variable deficient as a reflection of door to door travel time.

BT2 - a variant of BT1 with estimated waiting time included and hence, not assumed to be zero.

BTT - bus travel time, semi-engineered. This involved using the median of the reported travel time category when the bus was the chosen mode and the engineered value when not. Again, these variables will only be consistent if excess time is assumed zero.

BTT1 - bus travel time, semi-engineered. A variation of BTT with engineered bus time including estimated walks time within Livingston. Again, this is an attempt to achieve consistency between reported and measured values by relating both engineered and estimated values to total travel time, with wait time assumed zero. But the variable suffers from the non-availability of destination excess time information.

BTT2 - bus travel time semi-engineered. A variation of BTT1 but including waiting time, as estimated for within Livingston, and hence not assuming it to be zero. It still shows the same deficiencies, however.

COSTS

There were no reported costs for bus users and so the only semi-

engineered variables occur within car costs. Indeed, there is only one available form of bus costs:

BC - bus costs as estimated from fare tables including the costs of travel within Edinburgh when necessary.

CC, CC1, CC2 - car costs engineered as the product of measured distance and the cost per mile. For CC the cost per mile was the marginal cost (2.68 p); for CC1 the average variable cost (4.23p) and for CC2 the average total costs (9.85p).

CCOST, CCOST1, CCOST2 - car costs, semi-engineered, using the reported car costs when car was the chosen mode and the respective engineered costs CC1, CC2, CC3, when car was the non-chosen alternative. Variants of these variables were created where car passengers were allocated zero costs and half of the total cost.

TIME AND COST COMBINATIONS

Given the available time and cost variables, the following combinations of the time and cost variables were used to create the variables to enter the model. The difference forms of the variables are used as examples, the implications being the same for the other mathematical forms.

CT - BT: engineered car time less engineered bus time, relating to the in-vehicle travel time difference.

CT - BT1: engineered car time less engineered bus plus walk time pertaining to door to door time assuming car excess time as zero.

CT - BT2: engineered car time less engineered bus plus walk and wait time, a variation of CT - BT1.

CTT - BTT: semi-engineered car time less semi-engineered bus time pertaining to door to door travel time.

CTT1 - BTT1: semi-engineered car time less semi-engineered bus time. However, bus time was as reported when it was the chosen alternative but engineered bus and walk time when the non-chosen alternative. This relates to door to door travel time if car excess time is assumed zero.

Clearly all of these variable forms suffer from the deficiencies of their component parts as already considered.

CCn - BC: where n = 1,...,3 represents engineered car costs minus engineered bus costs for the different car cost estimates.
CCostn - BC: where n = 1,...,3 the semi-engineered version of the above.

In addition, similar variable forms were created with those individuals who were car passengers being allocated zero costs and half of the total costs.

5.8 SELECTION OF VARIABLE FORMS

Although arguments have been presented, both theoretical and more importantly, (in this study) practical, for the use of the engineered (measured) data rather than that derived from the reported values (semi-engineered), justification is still required empirically. To achieve this, a binary logit model for the car bus choice was estimated using only a constant and the various time and cost variable forms. This estimation procedure was carried out using 3 samples.

Sample 1	the total sample of individuals
Sample 2	a sub-sample comprising those individuals whose sample had at least one car available for use.
Sample 3	a sub-sample comprising only those individuals who were heads of households.

The use of these samples allows a comparison to be made of the behaviour of the various variable forms across the different samples. Further, the implications of differing coefficients for the same variable estimated across different samples can be considered.

In evaluating the behaviour of the various variables, the criteria used, both for comparison of the resulting models and the elimination of unacceptable models were:

1. The consistency of the sign of the coefficient estimate with the a priori expectations.
2. The level of significance of the coefficient estimates as regards the various t statistics.
3. The level of goodness of fit achieved by the models. For this purpose a number of goodness of fit measures were used (see Appendix 4). An aside being to evaluate the behaviour and consistency of these measures.

Table 5.1 illustrates the first stage of the analysis, the various time and cost difference variables for the three samples being evaluated on the basis of the first criterion. It appears that the only consistently well behaved variables are those which were engineered, the semi-engineered variables generally giving the wrong sign for the estimated coefficients in the various samples. This was not a surprising result given the deficiencies of the semi-engineered data, as previously considered and justifies concentration on the engineered variable forms for the rest of the study, given that the same pattern emerged when the estimation was performed for the different mathematical forms of the variables (namely, ratio, relative difference and log of ratios). These considerations together with the arguments already put forward in favour of using measured data, seem to imply that it will be necessary to use the engineered forms. As shall be seen, further support for this conclusion is provided by empirical estimation and evaluation.

An unfortunate feature of the results was the failure of the attempts to allocate some proportion of travel costs, either $\frac{1}{2}$ of the full cost or zero cost to those who were car passenger. This represents a clear deficiency of the study in that car passengers are allocated full journey costs, however, given the lack of information on cost allocation, and which drivers took passengers, etc., there is little that could be done to improve on this situation.

In assessing the performance of the various forms of the engineered variables, by the aforementioned criteria there are a number of considerations to be taken into account. Firtstly, it has already been

LEVEL OF SERVICE COMBINATIONS: DIFFERENCES TABLE 5.1

	CT-BT	CT-BT1	CT-BT2	CTT-BTT	CTT1-BTT1
CC-BC				1,2,3	1,2,3
CC1-BC				1,2,3	1,2,3
CC2-BC				1,2,3	1,2
CCOST-BC	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3
CCOST1-BC	2,3	2,3	2,3	1,2,3	1,2,3
CCOST2-BC	3	3	3	1,2,3	1,2
CCP-BC	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3
CCP1-BC	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3
CCP2-BC	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3

1=Combination of variables fails on criterion 1 for sample 1

2=Combination of variables fails on criterion 1 for sample 2

3=Combination of variables fails on criterion 1 for sample 3

noted that the combinations of CT and BT provide the most acceptable and self-consistent time variables. Thus, the other forms will only be considered if they can be shown to be markedly superior. Secondly, the combinations of CC and BC represent the commonly used forms of the cost variable, with CC reflecting the out of pocket, perceived cost of the car journey. The other cost variables simply imply different car costs per mile and will only be considered if they can be shown to improve the model. Finally, the difference form of the level of service variables will be used as the basis from which to evaluate the other mathematical forms. This results from the common acceptance of the difference variable (and its underlying implications) and its being implied by the derivation of the logit. As a result, model 1, in the following tables will be taken as the base model upon which the variations must be shown to improve for their further consideration.

Table 5.2 shows the coefficient estimates for the difference variable forms as estimated on the total sample. Each cost variable is fairly consistent as regards coefficient value and significance, when combined with the various time variables and the time variables differ in combination with the different cost variables. Hence, it would appear that the choice of cost variable appears to have more effect and to be more important than the time variable choice. All of the models are significant at the 5% level for the likelihood ratio test with fairly similar values for the goodness of fit statistics. Thus, it would appear that there is no reason to reject the base model, Model 1.

The various time variables reflect differing concepts of the travel time difference with CT - BT reflecting in-vehicle travel time, which CT - BT1 and CT - BT2 reflect total travel time, with excess time for car assumed zero and different assumptions made about excess time within Livingston. The implication of the similarity of the models, differentiated by the time variable form, are that the attempt to include origin excess time as a separate variable has been unsuccessful [1]. Such a conclusion is not surprising given the non availability of destination excess time and the planning of transportation facilities in Livingston. The fact that most dwellings within the town are within

1. **Thus, an attempt will be made to include excess travel time within Livingston as a separate variable.**

DIFFERENCES: TOTAL SAMPLE TABLE 5.2

MODEL NO.	1	2	3	4	5	6	7	8	9
CONST	1.001	1.537	1.830	1.045	1.551	1.787	0.192	1.325	1.481
	(2.208)	(2.275)	(2.173)	(2.161)	(2.235)	(2.104)	(1.514)	(1.696)	(1.646)
CT-BT	-0.019	-0.026	-0.033						
	(-1.056)	(-1.544)	(-1.950)						
CT-BT1				-0.014	-0.022	-0.028			
				(-0.823)	(-1.318)	(-1.725)			
CT-BT2							-0.015	-0.022	-0.029
							(-0.844)	(-1.346)	(-1.776)
CC-BC	-0.070			-0.073			-0.070		
	(-2.091)			(-2.169)			(-2.012)		
CC1-BC		-0.043			-0.043			-0.040	
		(-2.104)			(-2.128)			(-1.977)	
CC2-BC			-0.016			-0.015			-0.014
			(-2.002)			(-1.972)			(-1.840)
ITERATIONS	6	6	6	6	6	6	6	6	6
LLR	7.858	7.924	7.502	7.398	7.217	6.565	7.433	7.293	6.758
PSQ	0.028	0.028	0.027	0.026	0.026	0.023	0.026	0.026	0.024
LLI	0.029	0.029	0.027	0.027	0.026	0.024	0.027	0.027	0.025
APSQ	0.014	0.015	0.013	0.013	0.012	0.010	0.013	0.012	0.010
PSEUDO RSQ	0.035	0.036	0.034	0.033	0.032	0.030	0.033	0.033	0.030

400 metres of a bus stop implies that walk time could be relatively unimportant, while the infrequency of the services, implying individuals learn the schedules, appears to make the assumption of random arrival, as might hold in a city with frequent services, inappropriate.

The choice of engineered cost difference does appear to influence the fit and general significance of the models although not significantly. Indeed, the significance of the cost variables themselves differ little, while the difference in coefficient magnitude is purely the result of the scale factor introduced by varying the car cost per mile in computing the variable values.

When the same analysis was carried out for the sample of individuals whose household had at least one car (Table 5.3) the same pattern emerged as regards the influence of the time and cost variables on the choice of mode. All of the models are significant at the 5% level and although, as regards goodness of fit and general signficance, Model 7 appears superior. The difference between the models is marginal and there appears no reason to reject Model 1.

In comparing these results with those of Table 5.2, it would appear that the magnitude of the time coefficients has increased and are generally of greater significance while the value of the cost coefficients have decreased and have generally become less significant. These factors might imply that in considering those individuals who have access to a car the time difference between the car and bus is more successful in explaining the choice of car. This appears to be intuitively plausible as it might be expected that owning a car somewhat blinds the individual to its cost, or creates ignorance of the cost of the alternative mode. This might be considered to be underlined by the fact that the difference in significance between the cost variables with components CC and CC2, and their implied differing levels of rationality and cost awareness, is greater for the car available sample than for the total sample.

Comparing the goodness of fit of the models over the two samples is

DIFFERENCES: CAR AVAILABLE SAMPLE TABLE 5.3

MODEL NO.	1	2	3	4	5	6	7	8	9
CONST	1.289 (2.298)	1.631 (1.962)	1.715 (1.694)	1.189 (1.990)	1.499 (1.778)	1.590 (1.555)	0.840 (1.066)	1.016 (1.060)	1.058 (0.967)
CT-BT	-0.036 (-1.508)	-0.043 (-1.847)	-0.047 (-2.060)						
CT-BT1				-0.037 (-1.551)	-0.043 (-1.882)	-0.047 (-2.091)			
CT-BT2							-0.040 (-1.646)	-0.046 (-1.980)	-0.050 (-2.198)
CC-BC	-0.062 (-1.470)			-0.062 (-1.469)			-0.053 (-1.227)		
CC1-BC		-0.033 (-1.317)			-0.032 (-1.317)			-0.027 (-1.105)	
			-0.011 (-1.140)			-0.011 (-1.138)			-0.009 (-0.967)
ITERATIONS	6	6	6	6	6	6	6	6	6
LLR	6.684	6.278	5.852	6.826	6.417	5.987	7.178	6.900	6.616
PSQ	0.035	0.033	0.030	0.035	0.033	0.031	0.037	0.036	0.034
LLI	0.036	0.034	0.031	0.037	0.034	0.032	0.039	0.037	0.036
APSQ	0.018	0.016	0.014	0.019	0.017	0.015	0.021	0.019	0.018
PSEUDO RSQ	0.037	0.034	0.032	0.037	0.035	0.033	0.039	0.038	0.036

difficult as the log likelihood ratio is small for the second sample while the other statistics are larger. This results from the sensitivity of the log likelihood ratio statistics to the size of sample (See Appendix 4). The total sample would appear to produce superior results by this criteria.

Sample 3, containing only those individuals who were the head of their household, provided the estimates shown in Table 5.4. The same pattern, of the choice of cost variable being more important than the time variable, can be seen as in the previous sample. The models again differ little in goodness of fit and general significance with Model 3 being marginally superior to the others, and the only one significant at 5%. The closeness of the models however, would not seem to justify rejecting the base model.

In comparison with the estimates from the previous samples, a number of interesting points may be surmised. The general significance of the time variables is very poor when compared with the previous samples, while the significance of the cost variables is higher than in the second, car available sample. The coefficient values of the time variables are comparable with the first sample, but lower than the second, while those of the cost variables are higher than in both samples.

Though the decreased sample size has influenced the results, there are some intuitively plausible implications. It might be considered that the estimates reflect the higher level of rationality of heads of households, as regards costs of travel, as implied by the difference between the cost variables contianing CC and CC2 (with their different implications for cost awareness). Indeed, this might imply the head of household paying the fixed costs, and hence, being aware of them while other household members only need be concerned with the marginal costs. Thus, the head might be considered to require a greater awareness of the cost implications of mode choice and to give relatively less weight to time considerations.

Again, comparisons of the models across the sample as regards goodness

DIFFERENCES: HEADS SAMPLE

TABLE 5.4

MODEL NO.	1	2	3	4	5	6	7	8	9
CONST	1.736 (2.639)	2.573 (2.606)	3.212 (2.580)	1.805 (2.556)	2.067 (2.559)	3.168 (2.522)	1.788 (2.016)	2.493 (2.162)	2.914 (2.197)
CT-BT	-0.015 (-0.612)	-0.024 (-0.989)	-0.034 (-1.428)						
CT-BT1				-0.010 (-0.008)	-0.019 (-0.809)	-0.029 (-1.256)			
CT-BT2							-0.008 (-0.324)	-0.016 (-0.711)	-0.026 (-1.174)
CC-BC	-0.080 (-1.684)			-0.083 (-1.749)			-0.012 (-1.673)		
CC1-BC		-0.056 (-1.929)			-0.056 (-1.948)			-0.054 (-1.858)	
CC2-BC			-0.023 (-2.028)			-0.023 (-2.004)			-0.021 (-1.908)
ITERATIONS	6	6	6	6	6	6	6	6	6
LLR	4.615	5.569	6.050	4.408	5.213	5.507	4.335	5.053	5.285
PSQ	0.031	0.031	0.040	0.029	0.035	0.037	0.029	0.034	0.035
LLI	0.032	0.039	0.042	0.030	0.036	0.038	0.030	0.035	0.037
APSQ	0.010	0.017	0.020	0.009	0.019	0.016	0.008	0.013	0.015
PSEUDO RSQ	0.032	0.038	0.041	0.030	0.036	0.038	0.030	0.035	0.036

of fit is difficult. Although the sample size sensitive log likelihood ratios are worse, the other statistics would appear comparable. It might, however, be argued that better fits should be expected for the heads sample because of the higher level of homogeneity within the sample. However, the constant terms have relatively high coefficient values and levels of significance, and if this criteria is accepted, it counts against the comparative performance of the models [1]

The estimation results for the ratio form of the various engineered time and cost variables on the total sample, are shown in Table 5.5. The coefficient sign's magnitudes and significance are consistent for each of the time variables when combined with the various cost variables. This is not true of the cost variables when combined with the various time variables, though the main deviation is in the models containing CT and BT2 and it is this set of models which achieve the best goodness of fit measurements. Although all are significant at the 2.5% level. The marginal differences in general significance and goodness of fit, however, would appear to give little reason to reject the base model, Model 1.

In contrast to the difference forms of the variables, the time variables, although having lower significance than the cost variables appear to effect the models more, by their choice. Though, again not enough to overcome the reservations already put forward for the variables other than CT/BT. It is evident that the Models 1,2,3 are virtually identical as are 4,5, and 6 and 7,8 and 9; as regards goodness of fit and significance. This results from the fact that the cost variables CC, CC1, CC2 in only varying by the different cost per mile used are linearly related (of the form $\propto$(CC/BC), $\propto$ varying for each model).

The decrease in the importance of the cost variable, when compared with the results for the difference forms of the variables, probably relates to the form of the variables, the ratio form giving a lower magnitude than the other variable forms. The constant terms are both

1. **See Appendix 5.**

RATIOS: TOTAL SAMPLE TABLE 5.5

MODEL NO.	1	2	3	4	5	6	7	8	9
CONST	3.774 (3.159)	3.773 (3.159)	3.773 (3.159)	3.716 (3.136)	3.714 (3.136)	3.714 (3.136)	3.627 (3.124)	3.625 (3.123)	3.626 (3.124)
CT & BT	-1.465 (-1.247)	-1.466 (-1.248)	-1.465 (-1.247)						
CC & BT1				-1.415 (-1.119)	-1.416 (-1.119)	-1.415 (-1.119)			
CT & BT2							-2.429 (-1.467)	-2.430 (-1.468)	-2.429 (-1.468)
CC & BC	-1.581 (-1.669)			-1.610 (-1.687)			-1.196 (-1.140)		
CC1 & BC		-1.001 (-1.668)			-1.019 (-1.686)			-0.756 (-1.138)	
CC2 & BC			-0.430 (-1.669)			-0.438 (-1.686)			-0.325 (-1.139)
ITERATIONS	6	6	6	6	6	6	6	6	6
LLR	7.868	7.864	7.866	7.552	7.548	7.551	8.509	8.505	8.507
PSQ	0.028	0.028	0.028	0.027	0.027	0.027	0.030	0.030	0.030
LLI	0.029	0.029	0.029	0.028	0.028	0.028	0.031	0.031	0.031
APSQ	0.014	0.014	0.014	0.013	0.013	0.013	0.017	0.017	0.017
PSEUDO RSQ	0.035	0.035	0.035	0.034	0.034	0.034	0.038	0.038	0.038

significant and of high magnitude when compared to the results for the difference form. This is, however, the expected result, caused by the variable form in the model (See Appendix 5).

Tables 5.6 and 5.7 show the estimation results for the car available sample and the heads of household sample, respectively. They both portray very similar characteristics to the total sample estimates, and by analogous reasons do not appear to reject the choice of Model 1. They both show lower levels of significance to the sample estimates, decreasing with sample size and as in the difference form estimates, although the LLR decreases, the other goodness of fit statistics seem to imply a similar, if not better fit, than the total sample models. All of the models in Table 5.6 are significant at the 5% level, and all in Table 5.7 significant at the 10% level for the LLR test.

Table 5.8 illustrates the estimation results for the total sample using the relative difference forms of the time and cost variables. As expected given the results for the ratio variable forms, the time coefficient estimates are again fairly consistent in significance and magnitude when combined with the different cost variable. Hence, their choice seems to be of most importance.

Although the models including CT and BT2 show the highest levels of goodness of fit, the differences are marginal and not enough to overcome the deficiencies of this time variable. Again, there appears no reason to reject Model 1. All are significant at the 2.5% level for the LLR test.

In comparison with the previous model forms, the relative difference has higher general significance than the ratio result for the cost variable but less for the time variable. Both are inferior to that of the difference form. The goodness of fit achieved are marginally higher, generally, than both the difference and ratio models.

The same pattern emerges for the car available and head of household samples, as shown in Tables 5.9 and 5.10 respectively. Both

RATIOS: CAR AVAILABLE SAMPLE

TABLE 5.6

MODEL NO.	1	2	3	4	5	6	7	8	9
CONST	4.628 (2.993)	4.626 (2.993)	4.627 (2.993)	4.626 (3.006)	4.624 (3.006)	4.625 (3.007)	4.349 (2.900)	4.347 (2.900)	4.348 (2.901)
CT & BT	-2.188 (-1.457)	-2.189 (-1.458)	-2.188 (-1.457)						
CT & BT1				-2.586 (-1.563)	-2.568 (-1.563)	-2.568 (-1.563)			
CT & BT2							-3.830 (-1.717)	-3.832 (-1.718)	-3.830 (-1.717)
CC & BC	-1.400 (-1.132)			-1.278 (-1.016)			-0.685 (-0.482)		
CC1 & BC		-0.886 (-1.130)			-0.808 (-1.014)			-0.433 (-0.481)	
CC2 & BC			-0.381 (-1.131)			-0.347 (-1.015)			-0.186 (-0.482)
ITERATIONS	6	6	6	6	6	6	6	6	6
LLR	6.529	6.527	6.529	6.885	6.883	6.885	7.547	7.546	7.547
PSQ	0.034	0.034	0.034	0.036	0.036	0.036	0.039	0.039	0.039
LLI	0.035	0.035	0.035	0.037	0.037	0.037	0.041	0.041	0.041
APSQ	0.017	0.017	0.017	0.019	0.019	0.019	0.023	0.023	0.023
PSEUDO RSQ	0.036	0.036	0.036	0.038	0.038	0.038	0.041	0.041	0.041

RATIOS: HEADS SAMPLE TABLE 5.7

MODEL NO.	1	2	3	4	5	6	7	8	9
CONST	4.628 (2.762)	4.626 (2.762)	4.627 (2.762)	4.546 (2.752)	4.545 (2.752)	4.545 (2.752)	4.395 (2.714)	4.394 (2.714)	4.394 (2.715)
CT & BT	-1.952 (-1.128)	-1.952 (-1.128)	-1.952 (-1.128)						
CT & BT1				-1.921 (-1.026)	-1.922 (-1.026)	-1.921 (-1.026)			
CT & BT2							-3.312 (-1.306)	-3.313 (-1.307)	-3.312 (-1.306)
CC & BC	-1.511 (-1.111)			-1.528 (-1.111)			-0.933 (-0.598)		
CC1 & BC		-0.956 (-1.110)			-0.967 (-1.110)			-0.590 (-0.597)	
CC2 & BC			-0.411 (-1.111)			-0.416 (-1.111)			-0.254 (-0.598)
ITERATIONS	6	6	6	6	6	6	6	6	6
LLR	4.995	4.993	4.994	4.761	4.759	4.760	5.511	5.509	5.510
PSQ	0.033	0.033	0.033	0.032	0.032	0.032	0.037	0.037	0.037
LLI	0.035	0.035	0.035	0.033	0.033	0.033	0.038	0.038	0.038
APSQ	0.013	0.013	0.013	0.011	0.011	0.011	0.016	0.016	0.016
PSEUDO RSQ	0.034	0.034	0.034	0.033	0.033	0.033	0.038	0.038	0.038

RELATIVE DIFFERENCES: TOTAL SAMPLE TABLE 5.8

MODEL NO.	1	2	3	4	5	6	7	8	9
CONST	0.841 (1.440)	1.896 (1.564)	4.894 (1.551)	0.824 (1.295)	1.907 (1.517)	4.992 (1.496)	0.274 (0.319)	1.082 (0.709)	3.358 (0.929)
CT & BT	-1.039 (-1.270)	-1.037 (-1.263)	-1.076 (-1.256)						
CT & BT1				-0.964 (-1.146)	-0.962 (-1.141)	-0.963 (-1.138)			
CT & BT2							-1.474 (-1.473)	-1.479 (-1.475)	-1.491 (-1.482)
CC & BC	-2.109 (-1.602)			-2.162 (-1.637)			-1.631 (-1.135)		
CC1 & BC		-2.333 (-1.581)			-2.394 (-1.618)			-1.797 (-1.118)	
CC2 & BC			-3.527 (-1.545)			-3.626 (-1.563)			-2.696 (-1.088)
ITERATIONS	6	6	6	6	6	6	6	6	6
LLR	8.060	7.998	7.895	7.742	7.686	7.591	8.668	8.632	8.569
PSQ	0.029	0.028	0.028	0.028	0.027	0.027	0.031	0.031	0.030
LLI	0.029	0.029	0.029	0.028	0.028	0.028	0.032	0.032	0.031
APSQ	0.015	0.015	0.015	0.014	0.014	0.013	0.017	0.017	0.017
PSEUDO RSQ	0.036	0.036	0.035	0.035	0.034	0.034	0.039	0.039	0.038

RELATIVE DIFFERENCES: CAR AVAILABLE SAMPLE TABLE 5.9

MODEL NO.	1	2	3	4	5	6	7	8	9
CONST	1.256 (1.665)	2.304 (1.442)	5.367 (1.278)	1.049 (1.262)	2.017 (1.203)	4.845 (1.126)	0.338 (0.292)	0.944 (0.451)	2.720 (0.545)
CT & BT	-1.460 (-1.375)	-1.452 (-1.364)	-1.441 (-1.348)						
CT & BT1				-1.650 (-1.481)	-1.643 (-1.471)	-1.634 (-1.457)			
CT & BT2							-2.205 (-1.620)	-2.199 (-1.612)	-2.191 (-1.602)
CC & BC	-2.043 (-1.175)			-1.886 (-1.071)			-1.369 (-0.596)		
CC1 & BC		-2.293 (-1.173)			-2.118 (-1.069)			-1.318 (-0.598)	
CC2 & BC			-3.552 (-1.168)			-3.279 (-1.065)			-2.052 (-0.601)
ITERATIONS	6	6	6	6	6	6	6	6	6
LLR	6.664	6.661	6.655	7.014	7.013	7.008	7.594	7.598	7.602
PSQ	0.035	0.035	0.035	0.036	0.036	0.036	0.039	0.039	0.039
LLI	0.036	0.036	0.036	0.038	0.038	0.038	0.041	0.041	0.041
APSQ	0.018	0.018	0.018	0.020	0.020	0.020	0.023	0.023	0.023
PSEUDO RSQ	0.037	0.037	0.036	0.038	0.038	0.038	0.042	0.042	0.042

RELATIVE DIFFERENCES: HEADS SAMPLE

TABLE 5.10

MODEL NO.	1	2	3	4	5	6	7	8	9
CONST	1.267 (1.475)	2.177 (1.228)	4.651 (1.012)	1.235 (1.309)	2.172 (1.173)	4.731 (1.011)	0.453 (0.343)	0.967 (0.414)	2.277 (0.416)
CT & BT	-1.365 (-1.120)	-1.376 (-1.124)	-1.398 (-1.133)						
CT & BT1				-1.281 (-1.018)	-1.293 (-1.023)	-1.316 (-1.035)			
CT& BT2							-2.018 (-1.300)	-2.048 (-1.312)	-2.100 (-1.335)
CC & BC	-1.892 (-0.994)			-1.944 (-1.015)			-1.154 (-0.539)		
CC1 & BC		-2.048 (-0.958)			-2.109 (-0.982)			-1.211 (-0.504)	
CC2 & BC			-2.982 (-0.901)			-3.081 (-0.927)			-1.664 (-0.449)
ITERATIONS	6	6	6	6	6	6	6	6	6
LLR	4.837	4.771	4.669	4.593	4.530	4.431	5.369	5.375	
PSQ	0.032	0.032	0.031	0.031	0.030	0.030	0.036	0.036	0.035
LLI	0.033	0.033	0.032	0.032	0.031	0.031	0.037	0.037	0.037
APSQ	0.012	0.011	0.010	0.010	0.010	0.009	0.015	0.015	0.015
PSEUDO RSQ	0.033	0.033	0.032	0.032	0.031	0.031	0.037	0.037	0.036

significance and magnitude of the coefficient estimates are greater for the car available than the total sample, for the cost variables. The head's sample does have a lower general level of significance, for the cost variables, than the other samples and comparable ones to the total sample. In both samples, the time variables have lower magnitude and significance than in the total sample.

Again, the results given in Tables 5.9 and 5.10 reflect differences marginal enough to not require the rejection of the base model, Model 1. All of the models in Table 5.9 are significant at the 5% level for the LLR test, while most are significant at the 10% level in Table 5.10.

Table 5.11 illustrates the estimation results for the log of ratio form of the time and cost variables for the total sample. As in the ratio and relative difference forms the choice of time variable appears to be the most important. All of the models are significant at 10% for the likelihood ratio test and the differences between them in terms of general significance and goodness of fit are marginal. Thus, there is no reason to reject the base model, Model 1.

The same conclusion can be drawn for the car available (Table 5.12) and the heads samples (Table 5.13) with the levels of significance of the models, by the LLR test, diminishing with sample size.

5.9 CONCLUSIONS

From the previous analysis, the evidence does not appear to suggest the inadequacy of the base model containing CC and BC, CT and BT any differences between other models being marginal. The question now is whether or not the empirical results for the various mathematical forms of the variables support, or fail to provide evidence against, the use of the difference forms of the variables. In the interests of clarity, the base models for the various variable forms and the three samples are illustrated in Table 5.14.

It is evident that for each sample, the models differ only marginally in

LOG OF RATIOS: TOTAL SAMPLE TABLE 5.11

MODEL NO.	1	2	3	4	5	6	7	8	9
CONST	0.838	1.773	3.508	0.823	1.780	3.556	0.320	1.049	2.403
	(1.479)	(1.599)	(1.615)	(1.340)	(1.547)	(1.608)	(1.395)	(0.756)	(0.950)
CT & BT	-0.994	-0.995	-0.994						
	(-1.298)	(-1.298)	(-1.298)						
CT & BT1				-0.917	-0.917	-0.917			
				(-1.178)	(-1.179)	(-1.178)			
CT & BT2							-1.335	-1.336	-1.335
							(-1.494)	(-1.494)	(-1.494)
CC & BC	-2.026			-2.102			-1.602		
	(-1.603)			(-1.636)			(-1.152)		
CC1 & BC		-2.050			-2.099			-1.600	
		(-1.602)			(-1.635)			(-1.150)	
CC2 & BC			-2.051			-2.100			-1.601
			(-1.602)			(-1.636)			(-1.151)
ITERATIONS	6	6	6	6	6	6	6	6	6
LLR	8.102	8.097	8.100	7.785	7.781	7.784	8.708	8.705	8.707
PSQ	0.029	0.029	0.029	0.028	0.028	0.028	0.031	0.031	0.031
LLI	0.030	0.030	0.030	0.028	0.028	0.028	0.032	0.032	0.032
APSQ	0.015	0.015	0.015	0.014	0.014	0.014	0.017	0.017	0.017
PSEUDO RSQ	0.036	0.036	0.036	0.035	0.035	0.035	0.039	0.039	0.039

LOG OF RATOIS: CAR AVAILABLE SAMPLE

TABLE 5.12

MODEL NO.	1	2	3	4	5	6	7	8	9
CONST	1.272 (1.737)	2.185 (1.052)	3.879 (1.358)	1.084 (1.352)	1.931 (1.266)	3.506 (1.192)	0.450 (0.411)	0.996 (0.527)	2.014 (0.584)
CT & BT	-1.367 (-1.371)	-1.367 (-1.371)	-1.367 (-1.370)						
CT & BT1				-1.521 (-1.471)	-1.522 (-1.471)	-1.521 (-1.471)			
CT & BT2							-1.951 (-1.602)	-1.952 (-1.603)	-1.951 (-1.602)
CC & BC	-2.004 (-1.189)			-1.862 (-1.091)			-1.203 (-0.637)		
CC1 & BC		-2.002 (-1.188)			-1.859 (-1.090)			-1.200 (-0.635)	
CC2 & BC			-2.003 (-1.189)			-1.861 (-1.091)			-1.202 (-0.636)
ITERATIONS	6	6	6	6	6	6	6	6	6
LLR	6.614	6.612	6.614	6.948	6.945	6.947	7.507	7.506	7.507
PSQ	0.034	0.034	0.034	0.036	0.036	0.036	0.039	0.039	0.039
LLI	0.036	0.036	0.036	0.037	0.037	0.037	0.041	0.041	0.041
APSQ	0.018	0.018	0.018	0.020	0.020	0.020	0.023	0.023	0.023
PSEUDO RSQ	0.036	0.036	0.036	0.038	0.038	0.038	0.041	0.041	0.041

LOG OF RATIOS: HEADS SAMPLE TABLE 5.13

MODEL NO.	1	2	3	4	5	6	7	8	9
CONST	1.280 (1.534)	2.127 (1.313)	3.701 (1.172)	1.252 (1.375)	2.122 (1.254)	3.736 (1.157)	0.549 (0.441)	1.086 (0.513)	2.085 (0.545)
CT & BT	-1.290 (-1.129)	-1.291 (-1.129)	-1.290 (-1.129)						
CT1 & BT				-1.199 (-1.029)	-1.199 (-1.030)	-1.199 (-1.029)			
CT2 & BT							-1.796 (-1.294)	-1.796 (-1.295)	-1.796 (-1.295)
CC & BC	-1.861 (-1.006)			-1.910 (-1.027)			-1.181 (-0.570)		
CC1 & BC		-1.859 (-1.005)			-1.908 (-1.026)			-1.178 (-0.569)	
CC2 & BC			-1.860 (-1.006)			-1.909 (-1.027)			-1.180 (-0.570)
ITERATION	6	6	6	6	6	6	6	6	6
LLR	4.866	4.864	4.865	4.624	4.622	4.623	5.368	5.367	5.368
PSQ	0.033	0.033	0.033	0.031	0.031	0.031	0.036	0.036	0.036
LLI	0.034	0.034	0.034	0.032	0.032	0.032	0.037	0.037	0.037
APSQ	0.012	0.012	0.012	0.010	0.010	0.010	0.015	0.015	0.015
PSEUDO RSQ	0.033	0.033	0.033	0.032	0.032	0.032	0.037	0.037	0.037

SUMMARY OF RESULTS

TABLE 5.14

	DIFFERENCE	RATIO	RELATIVE DIFFERENCE	LOG OF RATIO
TOTAL SAMPLE				
CONST	1.001 (2.208)	3.774 (3.159)	0.841 (1.440)	0.838 (1.479)
TIME	-0.019 (-1.056)	-1.465 (-1.247)	-1.039 (-1.270)	-0.994 (-1.298)
COST	-0.070 (-2.091)	-1.581 (-1.669)	-2.109 (-1.602)	-2.026 (-1.603)
LLR	7.858	7.868	8.060	8.102
PSQ	0.028	0.028	0.029	0.029
CAR AVAILABLE				
CONST	1.289 (2.298)	4.628 (2.993)	1.256 (1.665)	1.272 (1.737)
TIME	-0.036 (-1.508)	-2.188 (-1.457)	-1.460 (-1.375)	-1.367 (-1.371)
COST	-0.062 (-1.470)	-1.400 (-1.132)	-2.043 (-1.175)	-2.004 (-1.189)
LLR	6.684	6.529	6.664	6.614
PSQ	0.035	0.034	0.035	0.034
HEADS SAMPLE				
CONST	1.736 (2.439)	4.628 (2.762)	1.267 (1.475)	1.280 (1.534)
TIME	-0.015 (-0.612)	-1.952 (-1.128)	-1.365 (-1.120)	-1.290 (-1.129)
COST	-0.080 (-1.684)	-1.511 (-1.111)	-1.892 (-0.994)	-1.861 (-1.006)
LLR	4.615	4.995	4.837	4.866
PSQ	0.031	0.033	0.032	0.033

terms of general significance and goodness of fit levels. The cost variable is more significant in the difference form for all of the samples, while the time difference variable is of lower significance except in the car available sample, though the differences are marginal. Overall, it would appear that the empirical evidence does not contradict the choice of the difference form of the time and cost variables.

Some previous studies have considered different mathematical forms for the time and cost variables. Quarmby (1967) was the first to consider the different implied comparative assessments in the mode choice decision process. He studied ratios, differences and log of ratio forms finding the difference formulation to be the best of the three. These alternatives were further analysed by Stopher and Lavender (1972) who found differences and log of ratios to be indistinguishable though both performed better than ratios. The relative difference form was employed by Watson (1974) in his inter-urban study, his choice of this variable form being based upon its implied comparative assessment of time and costs, which he considered to be the most realistic for his study.

In this study, the analysis using the time and cost variables in the models gives, despite the general significance of the LLR statistic, rather poor results. There seems to be little that can be said, empirically about the relative performance of the variables because the models differ little. For this reason, the arguments presented previously, for the use of the difference formulation hold sway and it is these variable forms which will be used in the rest of the study.

CHAPTER 6

THE JOURNEY TO WORK IN EDINBURGH: OTHER EXPLANATORY VARIABLES

6.0 INTRODUCTION

With the form of the time and cost variables for the model determined, it is necessary to consider other variables which are relevant to the study of mode choice behaviour. This requires considering the practical limitations of the available data and selecting the variables which can best represent the mode choice determinants in the model. To this end, estimations are made, for the total and car available samples, of the basic level of service model with each of the available variable forms combined with each available variable. The selection for the final model is incorporated into it. Finally, a similar process is undertaken for the heads sample and the final model forms assessed.

6.1 EXCESS TRAVEL TIME

The disaggregation of travel time into it's various components has already been discussed, as have the practical problems of estimating such values. Though it would clearly be desirable to consider the various components of the total, door to door, travel time, namely walk, wait, transfer and in vehicle travel time, the only estimates available for excess travel time were for within Livingston.

Attempts were made to use excess travel time estimates for within Livingston together with in vehicle travel time estimates to relate to total travel time. The improvement this afforded over the computationally more simple and satisfying in vehicle travel time estimates was, however, not adequate to weight opinion in favour of this approach. It is, however, worth considering the incorporation of these origin excess time values, in keeping with accepted practice as separate variables in the model, despite their failure to represent the whole of excess travel time.

To test the feasibility of this approach, the various excess time difference variable forms were estimated, on the assumption of zero car excess time, and used in models containing only the constant term, an in vehicle travel time difference variable, a cost difference variable and the relevant excess time variable.

The basic form of the excess time variables used were, to take walk time as an example:

car walk time = 0; excess time difference = (0-WALK)
bus walk time = WALK

The expected sign of the coefficient estimate is negative as an increase in excess time difference would imply an increase in walk time for car, or a decrease in that for the bus, and thus a decrease in the probability of choosing the car mode. The converse holding for a decrease in the value of the excess time difference.

Table 6.1 gives the estimation results for the following variables when integrated with the "basic level of service" model:

WALKD	=	estimated bus walk time substracted from zero car walk time
WAITD	=	estimated bus wait time substracted from zero car wait
WWD	=	estimated walk and wait substracted from zero car walk and wait time

For the total sample these excess time variables are insignificant, each having a t statistic of below 1.0, also the signs of the coefficient values for WALKD and WWD do not comply with a priori reasoning. In addition as the models are not significantly different from the base model [1], (combining only the level of service variables CT - BT and CC - BC). This attempt to include excess time has been unsuccessful.

The results for the car available sample, shown in Table 6.1 have the correct sign for the excess time variable coefficients but again are insignificant with t statistics below 1.0. In addition none of the models are significantly different from the original model (containing only CB - BT and CC - BC) for the LLR test. Clearly these results are an improvement over those obtained for the total sample, even though the excess time variables remain insignificant. That this should be the case is not surprising as the car available sample will exclude individuals who are bus captive riders and don't have access to a car.

1. **This test is based upon the difference between the LLR of the model with the 3 variables and that with 2 being distributed chi squared with 1 degree of freedom. Thus for nested models this test will determine whether or nor the models differ significantly, see Appendix 4. The estimation results for the base model are given in Table 5.14 in the previous chapter.**

EXCESS TIME VARIABLES

TABLE 6.1

	TOTAL SAMPLE			CAR AVAILABLE SAMPLE		
CONSTANT	1.202 (2.380)	0.694 (0.646)	1.370 (1.702)	1.168 (1.812)	0.276 (0.207)	0.555 (0.491)
CT-BT	-0.018 (-1.006)	-1.101 (-0.019)	-0.017 (-0.937)	-0.036 (-1.513)	-0.042 (-1.670)	-0.039 (-1.617)
CC-BC	-0.071 (-2.105)	-0.063 (-1.555)	-0.077 (-2.148)	-0.062 (-1.472)	-0.038 (-0.751)	-0.049 (-1.072)
WALKD	-0.068 (-0.920)			-0.047 (-0.369)		
WAITD		-0.035 (-0.315)			-0.116 (-0.836)	
WWD			-0.032 (-0.557)			-0.065 (-0.065)
ITERATIONS	6	6	6	6	6	6
LLR	8.711	7.957	8.166	6.833	7.376	7.268
PSQ	0.031	0.028	0.029	0.035	0.038	0.038
LLI	0.032	0.029	0.030	0.037	0.040	0.039
APSQ	0.013	0.010	0.011	0.013	0.016	0.016
PSEUDO RSQ	0.039	0.036	0.037	0.037	0.040	0.040
LLR DIFF	0.853	0.099	0.308	0.149	0.692	0.584

LLR DIFF= The difference between the reported LLR and that of the base model

That excess time variables do not appear to be significant determinants of mode choice is not surprising, given the fact that they only consider origin (within Livingston) excess time. In addition, however, as already considered, the design of Livingston, with it's transport orientated development, has been such that the distance to the nearest bus stop from most distances is minimal (400 metres or less), hence walk time at the origin might be expected to be important. The lack of frequency of services to Edinburgh, relative to a typical interurban study might be considered to further reduce the importance of excess time. The reasoning behind this being that because of low frequency, individuals are more likely to be aware of the scheduling of services and thus will not arrive randomly, as is assumed in estimating the wait times and might be a plausible assumption where frequencies are high. This is not to argue that infrequent services might be an advantage, in their diminishing wait times, but merely that the relevant wait time is that caused by service delay rather than by random arrival of travellers, and it is not possible to get information on service delay. Thus wait time might be important but the measured wait time variables available are not relevant.

As a result of these findings, it appears that it is not worthwhile using the available excess time values. It is worth noting, however, a number of points implied by the results. Firstly, where the variables have the correct sign, they also portray the expected higher weighting, as regards the coefficient magnitude, than the in vehicle time variables. This is consistent with the differential weighting of the components of travel time found in other studies. In addition, they might be considered to reflect the success of Livingston Development Corporation's policy of minimising walking time.

6.2 TRANSFERS

Whether or not a traveller is required to change modes in a journey relates to two aspects of that journey, namely the effect on comfort and convenience and the effect on excess time. Although for long journeys it is possible that transfers may be between different modes it

is likely that they will manifest themselves changing from one bus to another. Indeed the necessity of taking more than one bus for a journey may be considered one of the major drawbacks of public transport.

Although there was information available in the study on whether those who actually drove to work had to use a bus from their parking place to their work-place, it was not possible to determine such information where the car was the non chosen alternative. Thus transfers for the journey could not be considered, only those required for the bus journey. In actual fact, only four drivers actually reported that they had to change modes at their destination giving further justification to the concentration on bus transfers.

Because there was no reported information on whether or not individual commuters were required to transfer between buses when, or if they travelled by bus, it was necessary to determine this information. In estimating travel times or costs it was necessary to determine, from the routes of the available bus services and the reported destinations, whether or not the individual changed to another bus on arrival in Edinburgh. Thus, this information was used to create a transfer dummy variable which took the value of 1 when a transfer was required for the bus journey (whether bus was the chosen mode or not) and zero otherwise.

As this transfer dummy can be considered a proxy for the discomfort of the journey or at least that part related to an increase in the destination component of excess travel time and effort, it's coefficient estimate is a priori expected to be positive. Table 6.2 indicates that the model including the transfer dummy did achieve the correct sign for the variable for both the total and car available samples. However, the transfer dummy was not significant in either of the samples, although it performed better in the car available sample estimation. In addition including the transfer dummy can be seen to be not significantly different from the original model when the LLR test is applied. Also there is a noticeable decrease in the significance of the time difference variable caused by it's high correlation, -0.753, for the total sample and 0.757 for the car available sample.

	TOTAL SAMPLE		CAR AVAILABLE SAMPLE	
CONSTANT	1.025	1.369	1.351	1.387
	(2.249)	(2.651)	(2.395)	(2.319)
CT-BT	-0.011	-0.006	-0.022	-0.032
	(-0.466)	(-0.305)	(-0.725)	(-1.287)
CC-BC	-0.066	-0.039	-0.056	-0.049
	(-1.863)	(-1.020)	(-1.305)	(-1.001)
DTR	0.325		0.681	
	(0.466)		(0.690)	
DPK1		-0.726		-0.269
		(-1.859)		(-0.573)
ITERATIONS	6	6	7	6
LLR	8.078	11.432	7.186	7.015
PSQ	0.029	0.041	0.037	0.036
LLI	0.030	0.042	0.039	0.038
APSQ	0.011	0.023	0.015	0.014
PSEUDO RSQ	0.036	0.051	0.039	0.038
LLR DIFF	0.220	3.574	0.502	0.331

LLR DIFF= The difference between the reported LLR and that of the base model

These findings seem to imply that the transfer dummy explains little that is not already explained by the original model and is thus superfluous. It is, however, interesting to note that in the car available sample, the significance of the coefficient is higher than in the total sample. This might imply the higher sensitivity of car owners to bus transfers, although it might be simply that people facing a journey using more than one bus would be more likely to be car owners.

6.3 PARKING

The choice of car for the journey to work will clearly be influenced by the parking conditions that the individual traveller faces. If parking space has to be paid for, the total travel cost of the journey will be increased, if parking is not available at the work place destination, both travel time and cost may well be increased, with the heavily weighted excess time component being affected. The costs of parking will be out-of-pocket costs, unless some form of season ticket is available and will probably be open to little perception error, except for the individuals who don't use the car mode.

In the survey, details were available on parking conditions, but only as reported by drivers, i.e. those who chose car. Drivers were asked:

i. Whether they had a permanent private parking place at their workplace, and if they didn't where they parked
ii. the daily cost of parking
iii. the time taken to get from their parking place to their workplace
iv. whether they used a bus to get from their parking place to work. Only four replied that they did.

That the parking place was elicited from drivers only meant that such information was only available from those who had chosen the car mode and driven to work and not for each individual in the sample. In addition, it was not possible to ascertain or estimate the parking conditions facing individuals for whom the car was the non chosen

mode, i.e. the parking conditions they would have met if they had travelled by car (or could have done so). Thus, it was not possible to use the reported information in the study, for reasons of non convergence. See Apprendix 6.

Intuitively, one would expect parking conditions to have an important effect on the choice of mode, especially for the work journey, where a car, if chosen, and not used for work, would need to be left somewhere for the whole day. To incorporate such effects, however, requires the estimation of parking conditions for both car users and bus users and the necessary data was not available nor estimable.

It was possible to consider a proxy for parking difficulty based upon whether the work situation was in the city centre or not. This, however, requires assuming that it is more difficult to park in the centre than elsewhere in the city and does not allow for the provision of parking by employees which is a serious deficiency. Nevertheless the incorporation of a dummy variable taking the value of 1 if the individual's destination was central [1] and zero otherwise was attempted empirically, after further analysis of the reported parking information revealed that a centre/not centre dichotomy did exist.

Table 6.2 gives the estimation results for the models including the parking dummy. These estimates show this dummy variable to have the correct sign [2], a fairly significant coefficient for the total sample and to improve upon the original model by it's inclusion, the difference

1. **Central being defined by the Lothian Regional Council's restricted parking zones.**

2. **A negative sign is expected as one would expect that a central destination would give a lower probability of choosing car than a non-central one because of the constraints in parking.**

being almost significant at the 5% level for the LLR test. This is not true of the car available sample estimates for although the parking dummy has the correctly signed coefficient, it is not significant and the model is not significantly different from the original model. This might reflect the fact that parking conditions are not so important where individuals have access to a car, but just a likely, that those individuals who face parking difficulties are less likely to have bothered to purchase a car.

The parking proxy variable is somewhat problematic in that it can reflect other features besides parking in representing centre/not centre differences, such as excess time and type of employment. It is also fairly collinear to both the time and cost variables, and thus decreases their significance by it's inclusion. These considerations imply that the variable is an inadequate representation of parking conditions and so it will not be considered further.

The survey provided further information for car drivers on whether the car was used at work, and whether it was supplied by the employer if it was required at work. This information, however, suffered from the same problems as the parking information, namely that it was specific to car drivers and neither available, nor estimable, for other individuals in the sample. For these reasons it was not possible to incorporate the information into the model.

DeDonnea (1971) has argued that the choice of car might be influenced by other possible trip characteristics such as the time of day of the trip, which can influence parking problems and trip times (because of the level of congestion) and consumption externalities among people in the same neighbourhood. The former will be considered later but the effects of consumption externalities implying possible social pressures to use a specific mode, might be considered best represented by household socioeconomic variables. The alternative is to use some socioeconomic index for the origin, but this would seem somewhat ad hoc.

6.4 CAR AVAILABILITY

Although information was available on the number of cars owned by, or available to each household, there was no information on the number of individuals holding driving licences, the age of the household members, nor which household members used the cars, where available. Thus it was only possible to use information on car availability at the level of the household, a not unusual occurrence in transport studies.

Exactly how car availability should be treated in a study of mode choice is open to question. The first consideration is whether or not the choice of car ownership is considered to be exogenous to the mode choice decision. If exogenous then it is considered that the individual's choice of mode is made with the availability, or non availability of a car already established. It is a common assumption that the choice of mode is made independently of the car ownership choice, in the same way that it is assumed independent of residential location choice (both being taken as given). In the short run this assumption would appear to be justifiable and if valid would imply that to include respondents who did not have a car available for use in the sample used for the mode choice study would lead to biased results.

Thus if the choice of car ownership is considered exogenous it is necessary to consider a sample of individuals who, at least, had access to a car and hence, had the opportunity to choose between car and bus modes for the journey to work.

As mentioned, car available data was only available at the household level this begs the question as to how the use of the available cars is allocated wtihin the household. The use of the car would be related to:

i. individual specific use, where whoever owns the car will always be the one who uses it. This is probably a common occurrence, either the head of the household or spouse always having use of the family car, with dependants, if they have cars, having access only to their own car.

ii. there may be an hierarchical structure of car use, with the head of the household having first preference, spouse second preference and so on.

iii. there may be a simultaneous, or recursive choice structure for the allocation of car use within the household.

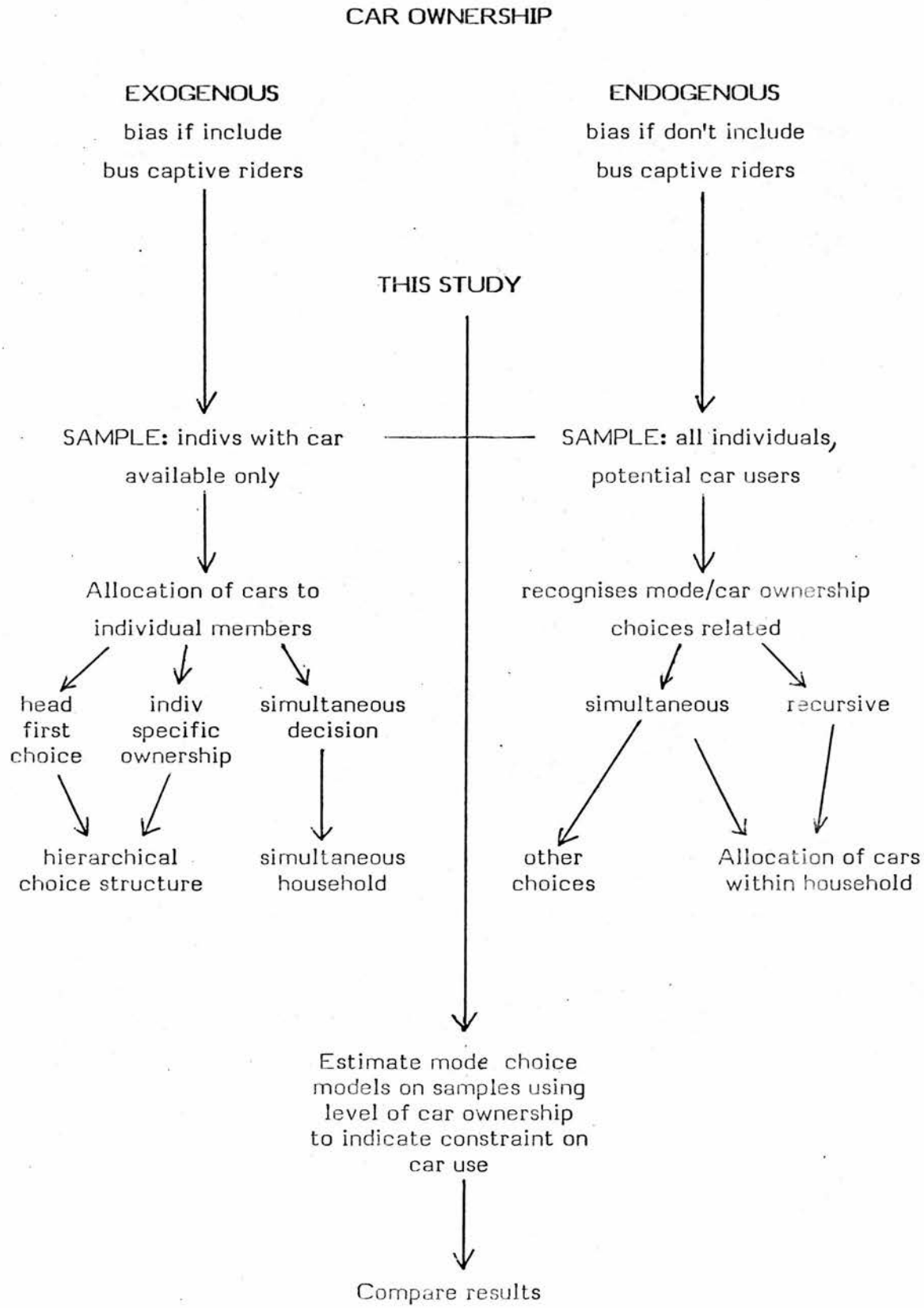
There are other factors which might warrant consideration such as the spouse having the car for shopping, taking children to school and other such activities, but not on a consistent basis. Car allocation might be complicated further by the effects of different levels of car ownership on the decision structure; necessity of use by individuals with differing priorities on different days of the week, individuals although not drivers affecting the allocations as passengers (i.e. joint trips), cars available being required for work or the cars being company cars and other such factors. Clearly the allocation of cars within households presents complicated problems for analysis, mainly outside the practical limitations of the present study.

On the other hand, if the choice of car ownership is considered to be endogenous, then the choice of car ownership will be related to the choice of mode. Thus, the non-inclusion of individuals without access to a car will bias the results. In this case, it is therefore necessary to use the whole sample, including captive riders.

The problem then to be considered is how the two choices, of car ownership and mode are related. There are a number of possible approaches to this problem, including:

i. to simply estimate a mode choice model on the total sample, including those individuals who have no access to car on the assumption that they could buy one if they wish to use that mode. This approach has the advantage of simplicity though not of realism, given the time dimensions of mode choice and car ownership. It does have the advantage, however, of countering the bias introduced by dropping bus captive riders (if the car

Fig. 6.1


CAR OWNERSHIP
EXOGENOUS
bias if include
bus captive riders
ENDOGENOUS
bias if don't include
bus captive riders
THIS STUDY
SAMPLE: indivs with car
available only
SAMPLE: all individuals,
potential car users
Allocation of cars to
individual members
recognises mode/car ownership
choices related
head
first
choice
indiv
specific
ownership
simultaneous
decision
simultaneous
recursive
hierarchical
choice structure
simultaneous
household
other
choices
Allocation of cars
within household
Estimate mode choice
models on samples using
level of car ownership
to indicate constraint on
car use
Compare results

ownership choice is considered endogenous) and doesn't require the loss of observations.

ii. to consider the mode/car ownership choice as a simultaneous choice and model it as such with mode choice dependent on car ownership and vice versa, and hence, a single choice:

iii. to consider the mode/car ownership choice as a recursive choice structure and model it as such:

$$P_{co,cm} = P_{cm \mid co} \times P_{co}$$

$P_{cm \mid co}$ = the probability of choosing a particular mode conditional on a particular car ownership level.

Which could include some form of feedback effect, for example, see Domencich and McFadden (1975). This approach will, however, require a particular choice structure to be assumed or derived, to decide on the direction of choice.

Of these approaches, the first is the simplest but also the least appealing in its disregard for the problems, both temporal and financial, of acquiring a car (although the second approach can be argued to be deficient in this respect) and it's implication that the car mode enters the choice set of those individuals who do not have a car available [1].

The second and third approaches might be considered more realistic but require the separate modelling of the two choices. They are both complicated if consideration is given to different levels of car ownership. Further, the second and third approaches can still be considered to require the consideration of the allocation of car usage within the household, as outlined for the case where car ownership is assumed exogenous. This would clearly make the analysis more

1. **This approach can be justified in this study by considering that because car passengers and drivers are not distinguished, it is still possible to consider individuals without a car available in the household to be potential car users.**

complex especially if there is concern for the way in which the car ownership and car allocation decisions are related and indeed how car ownership might be related to other travel decisions than the work trip.

In this study the practical limitations of data availability played an important part in the treatment of car availability. The lack of information on car allocation and individual specific car ownership variables precluded any but the most crude considerations of the car allocation within the household. Thus, this aspect of the choice mechanism was not considered.

To take account of the possibility of introducing bias by the non inclusion of bus captive riders, if the car ownership choice was found to be endogenous, the empirical analysis has been made on the basis of both the total sample (sample 1) subsample of individuals whose household owned at least one car (the car available sample, sample 2). The approach taken is illustrated in the context of the previous analysis in figure 6.1. Comparison of the results from the two samples was intended to give some idea of the importance of the assumptions made about car ownership and whether it could be worthwhile to pursue the analysis of the relation between car ownership and mode choice. The practical limitations of the data, whether it was adequate both in terms of available variables and the number of observations also have to be borne in mind. These aspects will be considered further in Chapter 10.

A further important practical question is the way in which the available information on car availability should enter the models as explanatory variables and what meaning they have. The candidate variables created were:

NCR - the number of cars owned by the household (or available). It is expected that an increase in the number of cars

would increase the probability of choosing car, and hence a positive coefficient is expected.

NCR1 - the number of cars per household members (NCR/NH) which as with NCR should have a positive coefficient.

NCR2 - the number of cars per full time employed member of the household (NCR/NFTE), again a positive signed coefficient is expected.

DNCR - a dummy variable which takes the value 1 if the individual has less than one car available and 0 other wise. This variable is meant to represent the effect of not having more than one car available and is in the form used by DeDonnea (1971). As a value of 0 is taken when more than one car is available, it is expected that the coefficient for the variable will have a negative sign.

NCR1 and NCR2 are intended to reflect the level of constraint on car use for the individual household member. As no information was available on the number of drivers, licence holders, or other aspects of car allocation, it was necessary to use the number of household members. The number of full time employed members with it's reflection on the age and financial standing of the individuals within the household was also used and tested, as it might be expected to better reflect the potential car users than simply the number of individuals in the household (which would also include children). These variables will, in addition, reflect the fact that some households do not own a car, by taking a value of zero and would be expected to be superior to NCR, the absolute number of cars in capturing the constraint on car use.

The results for the estimations, using the car available variables and the total sample, are shown in Table 6.3. All of the included variables have correctly signed and significant coefficients and their respective models show highly significant differences to the original model when the LLR tests is applied. As regards the comparative behaviour of the

CAR AVAILABILITY

TABLE 6.3

	TOTAL SAMPLE				CAR AVAILABLE SAMPLE			
CONSTANT	2.512 (3.408)	-1.489 (-2.375)	-0.922 (-1.569)	-1.688 (-2.505)	2.271 (2.869)	-0.816 (-1.096)	0.304 (0.434)	-0.203 (-0.220)
CT-BT	-0.024 (-1.290)	-0.043 (-1.901)	-0.043 (-1.972)	-0.047 (-2.037)	-0.041 (-1.642)	-0.040 (-1.605)	-0.043 (-1.706)	-0.042 (-1.658)
CC-BC	-0.066 (-1.940)	-0.058 (-1.474)	-0.067 (-1.809)	-0.051 (-1.524)	-0.059 (-1.383)	-0.056 (-1.256)	-0.064 (-1.497)	-0.058 (-1.371)
DNCR	-1.801 (-2.847)				-1.238 (-1.916)			
NCR2		3.763 (7.014)				2.867 (4.076)		
NCR1			5.529 (5.850)				2.422 (2.221)	
NCR				2.500 (6.041)				1.224 (1.926)
ITERATIONS	7	7	7	7	7	7	7	7
LLR	19.639	83.507	57.513	66.373	11.361	27.954	12.954	11.551
PSQ	0.070	0.297	0.204	0.236	0.059	0.145	0.065	0.060
LLI	0.075	0.422	0.257	0.309	0.063	0.170	0.070	0.064
APSQ	0.052	0.284	0.190	0.222	0.037	0.126	0.044	0.038
PSEUDO RSQ	0.086	0.317	0.231	0.261	0.061	0.145	0.068	0.062
LLR DIFF	11.781	75.649	49.655	58.515	4.677	21.270	5.907	4.867

LLR DIFF= The difference between the reported LLR and that of the base model

variables, it would appear to be consistent with expectations. NCR2, in terms of goodness of fit and significance levels performs best, while NCR performs better than NCR1 thus seeming to justify the reservations held about the latter variable. The relatively poor performance of DNCR is not surprising given the high proportion of one car owning households in Livingston, which is indeed, a common New Town characteristic.

The estimates for the car available sample in Table 6.3 differ a little from those for the total sample. All of the models are still significant at 1% confidence level by the LLR test and significantly different from the original model at the 1% level with NCR2 still performing better than the other variables. NCR1 is in contrast to the total sample, more significant than NCR while NCR differs little in terms of significance and goodness of fit from DNCR. These features clearly reflect the features of the sample. With all of the observations having at least one car available in their household DNCR will be more likely to pick up the effects of not having more than one car available, while the absolute number of cars NCR, given that it will always be at least one, will be less useful than in the total sample model and in general the constraint on-car use is expected to be less important. It is well worth noting that in the results for both samples, the introduction of the car availability variables would appear to have no significant effect on the significance and magnitude of the time and cost variables.

6.5 OTHER SOCIOECONOMIC DATA - HOUSEHOLD CHARACTERISTICS

The socioeconomic variables available at the household level, in the study, were:

NH - the number of individuals in the household

NFTE - the number of full time employed members of the household

NPTE - the number of part time employed members of the household

NU - the number of unemployed members of the household

NR - the number of retired members of the household

NC - the number of dependant members of the household (school-children or students).

There was no obvious reason why these variables should enter directly into the model. The effects of household size and the number of full time members employed have already been considered regarding the representation of the constraints on car use and are probably also related to social class.

Information was also available on social class of the household (SOCLH) and their socioeconomic group (SECON), both as is normal practice based upon the head of the household. It is possible that the social class and the socioeconomic group of the household could influence the choice of mode as they could reflect the consumption externalities of being in a specific social group or a social status effect. Although these features might be reflected in the number of cars owned by the household, it is still likely that the social status of the household will affect the behaviour of the individual members. In addition, social class might be considered closely correlated with and so serve as a proxy for household income levels. Indeed, as income levels are often inaccurately reported, social class, with the added advantage of representing non pecuniary effects, might be considered a more satisfactory socioeconomic variable. On the other hand, given the relative homogeneity, as regards socioeconomic characteristics, it is reasonable to expect that such variables as social status and occupation will not have so great an effect.

The variable forms created for the empirical analysis were:

DSOC - a dummy variable taking the value of 1 if social class was within the first three categories and zero otherwise. This represents a white versus blue collar distinction.

DSOC1 - a dummy variable taking the value of 1 if social class 1 and zero otherwise. This represents a professional, non professional distinction, one which might be considered important given the relative homogeneity of the sample under study.

DSEC - a dummy variable taking the value of 1 for employers, managers, professional workers, i.e., the first four socioeconomic groups and zero otherwise.

All of these variables will be expected to have positive coefficients, as one would expect the higher the social status of the household, the more likely the individuals would travel to work by car.

Table 6.4 gives a the estimation results for the models containing the relevant socioeconomic variables for both the total and the car available sample. All of the variables have the correct coefficient signs and in both samples the socioeconomic group dummy DSEC is insignificant, and hence inferior to both DSOC and DSOC1. In the total sample, estimates DSOC1 is more significant than DSOC, both the resultant models are significantly different from the null hypothesis and the original model at the 5% confidence level, with DSOC performing best. For the car available sample, the two variables differ little in significance and goodness of fit, neither being significantly different from the original model at the 5% confidence level.

That the social class variables should not perform as well in the car available sample as in the total sample estimates, is not surprising. In considering a sample of the individuals with car access, it would be expected that there would be some relation between social class and car ownership and hence the observations dropped would cause an increase in homogeneity as regards social class. This would also explain why DSOC and DSOC1 behave similarly in the car available sample, while DSOC1 is superior to DSOC in the total sample estimates.

HOUSEHOLD STATUS

TABLE 6.4

	TOTAL SAMPLE			CAR AVAILABLE SAMPLE		
CONSTANT	0.890 (1.903)	0.935 (2.025)	0.989 (2.180)	1.223 (2.101)	1.265 (2.220)	1.256 (2.242)
CT-BT	-0.020 (-1.118)	-0.021 (-1.139)	-0.019 (-1.047)	-0.037 (-1.517)	-0.039 (-1.566)	-0.035 (-1.475)
CC-BC	-0.093 (-2.603)	-0.078 (-2.293)	-0.074 (-2.160)	-0.084 (-1.898)	-0.071 (-1.676)	-0.068 (-1.594)
DSOC	0.573 (1.852)			0.489 (1.280)		
DSOC1		1.200 (2.090)			0.834 (1.273)	
DSEC			0.116 (0.354)			0.304 (0.723)
ITERATIONS	6	6	6	6	6	6
LLR	12.089	13.917	8.293	9.023	9.256	7.452
PSQ	0.043	0.050	0.030	0.048	0.049	0.039
LLI	0.045	0.053	0.030	0.050	0.051	0.040
APSQ	0.025	0.032	0.011	0.026	0.027	0.017
PSEUDO RSQ	0.054	0.062	0.037	0.050	0.051	0.041
LLR DIFF	4.231	6.059	0.435	2.339	2.572	0.768

LLR DIFF= The difference between the reported LLR and that of the base model

The introduction of the social class variables has little effect on the behaviour of the time and cost variables in terms of both coefficient significance and magnitude, implying they do add explanatory power to the model. The relative homogeneity of the Edinburgh commuters sample as regards social class, has meant that DSOC1 the professional/non professional dummy has, as expected, performed better than the white/blue collar variable.

6.6 OTHER SOCIOECONOMIC DATA - INDIVIDUAL CHARACTERISTICS

The individual characteristics available for the study were:

i the status of the employed individuals in the household which was coded as 1 = head; 2 = second employed; 3 = third employed and so on.

ii the sex and employment status of the individual household members which were coded as:

0 = student

1 = male full time employed

2 = male part "

5 = female full "

6 = female part "

In actual fact, the coding was wider but the above are based on the sample responses.

iii type of employment of the individual

iv occupation of the individuals

v the starting/finishing time of the individuals

Using this information, the following variables were created:

STATUS - with coding as above (i)

DST - a status dummy with value 1 for head of household and zero otherwise

SAE - with coding as above (ii)

DSAE - a sex and employment status dummy with value 1 if male full time employed and zero otherwise.

It is to be expected that the position of the individual within the household hierarchy could affect the probability of choosing the car and their access to the cars available. The head of the household may well have priority on car use for the work journey, with the other household members having levels of priority dependent of their position in the household. This would be reflected in STATUS, but the form of the variable, its having a discrete coding and the actual values (weights) having no specific meaning, detracts somewhat, from its usefulness. It can, however, be argued that the main effect of this nature will be the distinction between individuals who are heads of households, those who are not, which will be reflected in DST. Thus, although both variables are used, it is clear that DST will have the greatest interpretative value. It is expected that the higher the individual status, the higher the probability of car choice, thus STATUS would have a negative coefficient and DST a positive one.

The sex of the individual might affect the probability of choosing car, as women might have a lower psychological preference for driving, and might attach different importance to level of service characteristics than males. The main effects would, however, probably be related to the individual's status as the head of the household would tend to be male. It was this reasoning that lead to the inclusion of the sex and

employment status variables SAE and DSAE, DSAE reflecting the effect of the sex of the head of the household and SAE the general sex and employment status and implied priorities of the individuals. This latter variable is deficient, however, in that its coding is somewhat arbitrary and there is no obvious rationale for the implied weighting. It is expected that SAE will have a negative coefficient value and DSAE a positive one, the rationale being the same as for the status variables.

The estimation results for the total sample are shown in Table 6.5. All of the variables have the correct sign and all of the models are both significantly different from both the null hypothesis and the original model at the 1% level, for the likelihood ratio test. DSAE and SAE behave similarly as regards significance and goodness of fit, which, together with the fact that DST performs better, might imply that the main status effect is captured by distinguishing between heads of households and non heads. Indeed although STATUS is the most significant variable, given the reservations held about it, DST would appear to be the most useful variable to reflect the effects of the status of the individual.

For the car available sample, the estimation results shown in Table 6.5 exhibit similar features to the total sample results. Indeed the general significance and goodness of fit of the models is better. DST can, however, still be chosen in the same way as being the best of the variables considered.

One noticeable feature of the status variable results is that although they do not, by their introduction, substantially effect the magnitude of the time and cost coefficients, they do affect their significance, especially the time variable.

DOCC an occupation dummy taking the value 1 if administration, management, professional and zero otherwise.

This occupation dummy variable was created on the belief that it is possible that those individuals at the higher occupation codings would

INDIVIDUAL STATUS

TABLE 6.5

	TOTAL SAMPLE				CAR AVAILABLE SAMPLE			
CONSTANT	3.029 (4.835)	0.010 (0.199)	1.601 (3.193)	0.310 (0.613)	4.956 (5.253)	0.352 (0.548)	2.306 (3.510)	0.437 (0.697)
CT-BT	-0.012 (-0.626)	-0.012 (-0.610)	-0.010 (-0.563)	-0.013 (-0.709)	-0.025 (-0.908)	-0.016 (-0.613)	-0.022 (-0.889)	-0.024 (-0.991)
CC-BC	-0.073 (-2.036)	-0.062 (-1.725)	-0.060 (-1.728)	-0.058 (-1.687)	-0.100 (-1.975)	-0.068 (-1.386)	-0.047 (-1.059)	-0.043 (-0.970)
STATUS	-1.272 (-5.281)				-1.950 (-5.918)			
DST		1.530 (4.892)				2.493 (5.701)		
SAE			-0.258 (-3.327)				-0.394 (-4.121)	
DSAE				1.038 (3.353)				1.401 (3.638)
ITERATIONS	6	6	6	6	7	7	7	7
LLR	40.821	32.901	18.975	19.180	55.682	46.317	24.100	20.165
PSQ	0.145	0.117	0.068	0.068	0.289	0.240	0.126	0.105
LLI	0.170	0.132	0.073	0.073	0.407	0.317	0.144	0.117
APSQ	0.129	0.100	0.051	0.051	0.273	0.223	0.106	0.084
PSEUDO RSQ	0.170	0.139	0.084	0.084	0.267	0.228	0.127	0.107
LLR DIFF	32.963	25.043	11.117	11.322	48.998	39.633	17.416	13.481

LLR DIFF= The difference between the reported LLR and that of the base model

be more likely to own a car. There are problems with this variable, however, as it is highly correlated to the social class and status of the individual, also the occupatoin of the commuters to Edinburgh are fairly homogeneous within the administration, managemen t and professional brackets. The results of the estimations in Table 6.6 show DOCC to be fairly significant in both the total and car available samples and though significantly different from the null hypothesis, it is only significantly different to the original model at the 5% level for the total sample.

Although the variable is available at the individual level because of the large numbers of heads of households in the sample, it is highly correlated with the household social class variable, which was based on the head of househod. Thus, a choice has to be made between DOCC and DSOC1 and the superior performance of DSOC1 as shown in Table 6.4 leads to the rejection of DOCC.

DSF, a dummy variable taking the value of 1 if the individual undertook the work journey at peak hours and zero otherwise.

This variable was an attempt to capture the influence of time of day of travel on mode choice resulting from problems of congestion and parking difficulties and the advantage of buses in using bus lanes. If this reasoning is accepted, the expected coefficient sign will be negative.

The results in Table 6.6 show DSF to have a negative sign in both the total and car available samples and to be fairly significant. The models are both significantly different to the null and the original model at the 5% level. Further, the introduction of the variable has little effect on the magnitude and significance of the time and cost variables and so would appear to add to the explanatory power of the model. It is interesting that the variable performs better for the car available sample implying that those with a car available are more sensitive to the problems created by rush hour travel. It is, however, possible to argue that those individuals who don't travel in the rush hour are more likely to be car owners, and so care must be taken in interpretation.

OCCUPATION/START AND FINISH TIME

TABLE 6.6

	TOTAL SAMPLE		CAR AVAILABLE SAMPLE	
CONSTANT	0.859 (1.860)	1.226 (2.535)	1.132 (1.981)	1.884 (2.999)
CT-BT	-0.019 (-1.038)	-0.020 (-1.089)	-0.035 (-1.449)	-0.029 (-1.212)
CC-BC	-0.071 (-2.104)	-0.070 (-2.063)	-0.062 (-1.473)	-0.058 (-1.320)
DOCC	0.571 (1.648)		0.634 (1.436)	
DSF		-0.573 (-1.920)		-1.129 (-2.999)
ITERATIONS	6	6	7	7
LLR	10.573	12.175	8.820	15.529
PSQ	0.038	0.044	0.046	0.081
LLI	0.039	0.046	0.048	0.088
APSQ	0.020	0.026	0.024	0.060
PSEUDO RSQ	0.047	0.055	0.048	0.084
LLR DIFF	2.715	4.317	2.136	8.845

LLR DIFF= The difference between the reported LLR and that of the base model

Before moving on to the analysis of the results for the heads sample, it is worthwhile summarising the results provided by the previous analysis.

6.7 SUMMARY OF TESTS ON CANDIDATE EXPLANATORY VARIABLES

It would appear that the attempts to include variables to reflect the excess time components of the journey have not been successful. Although the attempts to use excess time within Livingston implied the success of the design of the New Town to minimise walk times, the lack of information on destination excess time and the failure of the transfer dummy, DTR, as a proxy, due to the collinearity with the time variable, precluded any further study of this journey characteristic. Although this is unfortunate, given the high weighting for excess time components found in various studies, these characteristics are very difficult to derive, especially in forecasting, and are often, of necessity, excluded when models are used for predictive purposes.

In adition to implying the lack of importance or origin excess time, the excess time variables also behaved better for the car available sample. This might be considered to reflect the increased sensitivity of this sample to excess time, resulting from the exclusion of captive bus riders. The transfer dummy was also found to be more significant in the car available sample with similar implications, although it could be argued that individuals facing more than one bus for a journey or high excess time would be more likely to own a car.

The creation of a dummy variable to reflect a centre/not centre destination dichotomy, with regard to the implications for parking restrictions, appeared to have been fairly successful. The collinearity with the time and cost variables was not excessive and the variables took the correct sign in both samples, although it was not very significant with the car available sample. This might imply that having a car available for use would make the commuter less sensitive to parking conditions at the destination. The causality of this reasoning is, however, open to question as it might be argued that individuals who

face parking difficulties are less likely to own a car. In addition, the use of such a proxy variable might also pick up features other than parking for example, type of employment or indeed, destination excess time which would clearly detract from its interpretative value. For these reasons, it was decided not to consider the variable further.

As regards the household socioeconomic characteristics, it is unfortunate that no information was available on household income levels. However, when the usual problems connected with reported income data, such as non-response and bias are taken into account, the use of social class or socioeconomic data appears justified. This was supported by the empirical behaviour of the social class summy variables with the professional/non professional variable (DSOC1) being correctly signed, significant and a clear improvement over the original model. That this variable should perform better than the white/blue collar dummy was no surprise given the generally high social status of the Edinburgh commuters. The poorer performance of these variables in the car available sample might be considered to reflect the relations between social class and car ownership with households of high status being more likely to have one or more cars.

When considering the introduction of individual characteristics into the model DST, the dummy variable reflecting the head/not head of household distinction was found to be the most acceptable. This implied that the priority of the head of household to car use was an important determinant of car choice, the failure of DSAE (which was 1 for male head and zero otherwise) implying the sex of the head of household was not so important. Not surprisingly, the variables performed better for the car available sample further reflecting the importance of the heads priority on car use when a car was available.

The consideration of an occupation dummy variable reflecting the difference between administration, management and professional groups and others, was motivated by the desire to include the implicit socioeconomic features at an individual level. Thus, DOCC was in direct competition with the social class variables although these were

based on the head of household. Empirically, DSOC1 was found to be superior to DOCC and hence was chosen.

Start and finish times were entered into the model in the form of peak/non peak travel time dummy variable and found to be significant and acceptable if the rationale for its inclusion is accepted. Although these are problems of interpretation resulting from the fact that travelling during the rush hour will effect both car and bus, the rationale presented and the negative sign for the estimated coefficient implied that travelling at peak hours decreases the probability of choice of car.

The complex problem of car ownership, its effect on mode choice and their interrelationships were considered. In the study, the models were estimated on the total sample and a subsample of individuals with a car available for use to reflect the endogeneity/exogeneity of the choice process and to possibly identify any obvious bias caused by the inclusion or exclusion of captive riders.

Of the variable forms which attempted to reflect the leve of constraint on individual's car usage within the household NCR2, the number of cars per full time employed person performed best. Despite the deficiencies of this approach to introducing the car ownership effects, the variable was found to be highly significant. As expected the car constraint variables were less significant in the car available sample reflecting the loss of captive riders and the lower sensitivity to cost factors of this sample.

6.8 VARIABLE SELECTION FOR HEADS OF HOUSEHOLD

The heads of households represent 68% of the total sample and, as has been noted in a number of instances, can be considered to differ in behaviour to those individuals who are not heads of households. For these reasons, it would appear worthwhile to develop a separate mode choice model for the heads with a similar methodology and generally the same candidate explanatory variables as for the total and car available samples.

EXCESS TRAVEL TIME: HEADS SAMPLE

TABLE 6.7

CONSTANT	2.016 (2.712)	2.487 (1.536)	2.660 (2.201)	1.698 (2.548)	2.360 (2.871)	
CT-BT	-0.014 (-0.552)	-0.011 (-0.431)	-0.011 (-0.407)	-0.028 (-0.809)	0.005 (0.154)	
CC-BC	-0.082 (-1.719)	-0.098 (-1.629)	-0.099 (-1.877)	-0.087 (-1.766)	-0.040 (-0.745)	
WALKD	-0.089 (-0.852)					
WAITD		-0.084 (-0.508)				
WWD			-0.076 (-0.926)			
DTR				-0.498 (-0.543)		
DPK1					-1.036 (-1.738)	
ITERATIONS	6	6	6	6	6	6
LLR	5.308	4.877	5.448	4.907	7.911	
PSQ	0.036	0.033	0.036	0.033	0.053	
LLI	0.037	0.034	0.038	0.034	0.056	
APSQ	0.008	0.005	0.009	0.005	0.026	
PSEUDO RSQ	0.036	0.034	0.037	0.034	0.054	
LLR DIFF	0.693	0.262	0.833	0.292	3.296	

LLR DIFF= The difference between the reported LLR and that of the base model

As the results for the heads sample, in Table 6.7 show, the attempts to include excess time variables, or proxies of such, have been as unsuccessful as for the other samples. Although, in this case, the origin excess time variables WALK, WAITD and WWD have the correct signs and by their coefficients, imply the higher weighting of the excess component of travel time, they are singularly insignificant. That the variables do behave better than in the previous sample's estimations and have larger coefficients might tentatively be considered to imply the greater sensitivity of heads of households to excess travel time. Considering the priority of heads of household over car use within the household makes this a reasonable implication.

The transfer dummy fails to achieve the correct sign for its coefficient estimate and was found to be highly collinear with the time difference variable, as well as being insiginficant. Further although DPK1, the other level of service proxy, ws fairly significant and was significantly different from the original model at 10% level for the likelihood ratio test it forced the time difference variable to take the wrong sign. This has similar implications to the results for the other samples with either heads of households priority on car usage makes them less sensitive to parking conditions or that those facing adverse parking conditions are less likely to be car owners.

As shown in Table 6.8, the variables reflecting the constraint on car use perform remarkably well with all, excepting DNCR, being highly significant and their models differing very significantly from the original model. In attempting to estimate a model with DNCR included, the estimation procedure failed to converge which simply reflects the high incidence of car ownership (see Appendix 6). The behaviour of the other variables would seem to support the reasoning that where a car is available, the head of household will tend to have priority for use, especially when the results are compared to those of the car available sample, where their effects are much less.

In comparing the behaviour of the car constraint variables, it is clear the results differ from those of the previous samples. In terms of

CAR AVAILABILITY AND STATUS: HEADS SAMPLE

TABLE 6.8

CONSTANT	-0.284 (-0.330)	-0.549 (-0.603)	-1.463 (-1.298)	1.844 (2.668)	1.620 (2.440)	1.802 (2.710)
CT-BT	-0.027 (-0.858)	-0.032 (-0.928)	-0.038 (-0.914)	-0.015 (-0.605)	-0.018 (-0.708)	-0.019 (-0.753)
CC-BC	-0.095 (-1.661)	-0.112 (-1.887)	-0.141 (-2.178)	-0.078 (-1.618)	-0.079 (-1.676)	-0.078 (-1.623)
NCR2	3.590 (5.491)					
NCR1		10.755 (5.333)				
NCR			4.606 (5.799)			
DSOC				-0.238 (-0.556)		
DSOC1					0.664 (0.832)	
DSEC						-0.485 (-1.088)
ITERATIONS	7	8	8	6	6	6
LLR	47.616	58.407	75.011	5.153	5.627	5.999
PSQ	0.318	0.391	0.502	0.035	0.038	0.040
LLI	0.467	0.641	1.007	0.036	0.039	0.042
APSQ	0.299	0.373	0.487	0.007	0.010	0.012
PSEUDO RSQ	0.283	0.335	0.408	0.036	0.039	0.041
LLR DIFF	43.001	53.792	70.396	0.538	1.012	1.384

LLR DIFF= The difference between the reported LLR and that of the base model

significance, both coefficient and model, NCR, the number of cars in the household clearly performs better than NCR1 and NCR2. This might be considered to add further evidence to the priority of heads of households for car use, as the number of cars per person (or full time employed persons) can be considered to be of less importance, than simply the availability of one or more cars due to the heads priority on use. NCR does not, however, have the same interpretative value as NCR2 which reflects the constraint on car use in the household, NCR simply being the absolute number of cars. For this reason, NCR2 is to be preferred.

As regards the behaviour of the household social status variables illustrated in Table 6.8, it must be remembered that the social class and socioeconomic groupings are determined on the basis of the head of household. Thus, in this sample, DSOC, DSOC1 and DSEC are in actual fact individual specific. DSOC1 reflecting the professional/non professional distinction, takes the correct sign and behaves better than DSOC implying the generally high level of social status of the commuters especially among the heads sample. Indeed, it is probably the degree of homogeneity of this sample which causes these variables to behave badly and worse than in the previous samples, in terms of both coefficient and model significance.

In dealing with the heads of household sample, it is clear that the previous variables relating to the status of the individual, within the household, are redundant. This does, however, seem worthwhile to consider the sex and employment status variables which might reflect the differing behaviour of male and female heads of households. As can be seen in Table 6.9 both SAE, despite its arbitrary coding and DSAE are significant and their models differ from the original model at the 5% level for the likelihood ratio test. Clearly, SAE has little interpretive value, and the majority of the heads in the sample are male, but one might tentatively conclude that the results would support the reasoning that male full time employed heads of household are more likely to use a car.

INDIVIDUAL CHARACTERISTICS: HEADS SAMPLE

TABLE 6.9

CONSTANT	2.206 (3.130)	0.306 (0.326)	1.773 (2.610)	1.771 (2.579)
CT-BT	-0.015 (-0.563)	-0.012 (-0.471)	-0.016 (-0.633)	-0.028 (-1.006)
CC-BC	-0.069 (-1.430)	-0.070 (-1.459)	-0.079 (-1.664)	-0.075 (-1.538)
SAE	-0.430 (-2.055)			
DSAE		1.586 (2.367)		
DOCC			-0.163 (-0.377)	
DSF				-0.554 (-1.276)
ITERATIONS	6	6	6	6
LLR	8.962	9.913	4.676	7.409
PSQ	0.061	0.068	0.031	0.051
LLI	0.065	0.073	0.032	0.053
APSQ	0.034	0.041	0.003	0.023
PSEUDO RSQ	0.062	0.068	0.032	0.051
LLR DIFF	4.347	5.298	0.061	2.794

LLR DIFF= The difference between the reported LLR and that of the base model

Considering the final two candidate explanatory variables, as can be seen in Table 6.9, DOCC the occupation dummy, fails to achieve the correct sign, which is not surprising considering the behaviour of the social status variables for the heads sample. DSF, the start and finish time dummy, is, however, correctly signed and significant and its model is significantly different from the original model at the 5% level. It does not, however, perform as well as in the total and car available samples.

6.9 FINAL MODEL FORMS

From the previous analysis of the candidate explanatory variables, the final model forms decided upon included in addition to the constant and the time and cost difference variables:

1. for the total sample NCR2, DSOC1, DST, DSF

2. for the car available sample NCR2, DSOC1, DST, DSF

3. for the heads sample NCR2, DSOC1, DSF.

The estimation results for heads sample, however, gave an insignificant coefficient value for DSOC1 and its exclusion from the models, for all samples had little effect on both the likelihood ratio and the individual parameter estimates (the nested likelihood test showing the addition of DSOC1 to be insignificant). Although this might not justify the exclusion of DSOC1 if there was a priori justification for its inclusion, the variable represents a proxy for hypothetical income and social status effects. For this reason, its insignificance reflects its failure to fulfill such a role and this provides justification for excluding it.

DSOC1, the household social class dummy, is actually based upon the head of household, thus its failure to attain significance might be seen to imply that any social class effect is picked up by the other socioeconomic variable, NCR2. On the other hand, it might imply that DSOC1 in the other sample, picks up a social class effect which is head

FINAL MODEL FORMS

TABLE 6.10

	TOTAL SAMPLE	CAR AVAILABLE	HEADS SAMPLE
CONSTANT	-1.525 (-2.147)	0.120 (0.139)	-0.164 (-0.182)
CT-BT	-0.030 (-1.227)	-0.011 (-0.386)	-0.038 (-1.091)
CC-BC	-0.072 (-1.698)	-0.085 (-1.650)	-0.089 (-1.496)
NCR2	3.562 (6.281)	1.482 (2.173)	3.704 (5.341)
DSDC1	1.533 (2.266)	1.437 (1.905)	
DST	1.169 (2.963)	2.081 (4.286)	
DSF	-0.869 (-2.120)	-1.099 (-2.387)	-1.026 (-1.828)
ITERATIONS	7	7	8
LLR	102.769	59.376	49.765
PSQ	0.374	0.316	0.341
LLI	0.598	0.461	0.517
APSQ	0.353	0.287	0.317
PSEUDO RSQ	0.381	0.288	0.297

of household specific. In other words, the probability of choosing car is dependent on the social class of the head of household.

The estimation results for the final model form are shown in Table 6.10. As a check on the effect of varying the definition of car costs, the models were also estimated using the cost variables based upon marginal costs, average variable costs and average fixed costs per mile. The different cost variables appeared to have minimal effects on the models, with the goodness of fit measures similar and the non-level of service variable parameters similar. The only changes were in the level of service variables which reacted to the redefinition of the costs by reflecting the scale factor involved in the different computations.

The final model forms are highly significant in terms of their difference from the null hypothesis and their explanatory variables are generally significant and invariably correctly signed. Further, examination of their correlation coefficient matrix showed multicollinearity not to be a problem (using DeDonnea (1971) criteria of a value of 0.7 showing significant collinearity). The results do, however, seem to imply that the probability of choosing the car mode is determined by factors other than the relative times and costs of the modes. Indeed, when the models were estimated without the time and cost variables, the LLR values were 96.331 for the total sample, 55.832 for the car available sample and 43.617 for the heads sample. Using the nested LLR test, this implies that the model including time and costs is just significant at 5% but not at 2.5% for the total and heads sample and not significant even at 10% for the car available sample. Given the a priori reasoning for the inclusion of the time and cost variables, this does not provide justification for dropping the variables. It does, however, indicate the importance of other factors.

The time and cost variables are correctly signed and interestingly, the cost variable is more significant than the time variable. This is especially true for the car available sample where it is the result of the low significance of the time variable. This implies that when only those with a car available are considered, the difference in time between car

and bus has less effect on mode choice. This seems reasonable given the significance of NCR2, which implies that the more cars per full time employed, the higher the probability of choosing the car, but it is surprising that the relative cost of the car should be so much more significant. One might expect that the availability of a car blinds the individual to the cost of the car should be so much more significant. One might expect that the availability of a car blinds the individual to the cost of using it. Although the reslt is more plausible given that the cost considered are the marginal, out of pocket costs, which are directly perceivable. For the heads sample, it could be argued that the head of household is more likely to bear the car costs, even if he or she doesn't use the car.

NCR2 is significant for all three samples and as expected, lowest in significance for the car available sample. DSOC1 is significant for the total and car available sample implying some social status effect within these samples, possibly related to income levels but as noted its failure in the heads sample might imply a more specific influence. The significance of the heads model and the significance of DST in the total and car available samples shows that whether or not the individual is a head of their household is an important influence on mode choice. It is interesting that DST is more significant for the car available sample as this implies (together with the significance of NCR2) that when a car is available the head of household will have priority of use. Finally, DSF is significant for the total and car available samples and fairly significant for the heads sample. Thus, the time of travel is a significant influence on mode choice, a feature which is to be expected given the nature of the journey to Edinburgh where not only the conditions of efficient travel within Livingston have to be considered, but also the bus efficient routes to a Edinburgh and the conditions met at the destination. It would appear that there is a bias away from choice of car, if the work journey is in the rush hour.

Although the comparative assessment of the models over the different samples is problematic, because of the different specifications for the heads sample, the models do provide a useful analysis of the journey to

work between Livingston and its nearest city, Edinburgh and raise some interesting points. These results will be considered further in Chapter 10.

CHAPTER 7

THE JOURNEY TO WORK WITHIN LIVINGSTON

7.0 INTRODUCTION

This chapter builds upon the analysis undertaken in the previous two chapters to provide an empirical study of mode choice for the journey to work within Livingston. This is clearly an important analysis, given the extreme form of Livingston New Town characteristics. It also allows the consideration of walking as an important alternative to both bus and car. This is clearly a novel feature for analysis and one with important implications for transport planning in general. For the analysis the model of the previous two chapters has to be generalised to allow consideration of three modes. This multinomial model has already been outlined in Chapter 4 and Appendix 9 presents the program used for estimation.

Building upon the analysis of Chapter 5, the first section presents an analysis of, and estimation results for, the level of service variables. Section two then presents the analysis and selection of the socioeconomic variables. Section three gives the final forms of the models, and assesses their implications. Finally, section four compares the results with those for the journey to work in Edinburgh.

7.1 LEVEL OF SERVICE VARIABLES

In considering the forms of the level of service variables for the analysis of mode choice within Livingston, many of the problems encountered have already been analysed within the context of the previous study of mode choice between Livingston and Edinburgh. This section draws heavily upon the arguments presented within that study, in Chapters 5 and 6.

Given the problems of coding already experienced, it was clear that the available reported time and cost data were even less satisfactory for this study. The main complaint in the previous study was the inexactitude of the coding categories and this problem is clearly exascerbated by the much smaller trip lengths of the journeys within the New Town. Thus, only the engineered (measured) were considered.

In-vehicle travel times for the car mode were computed for each journey by measuring the distance between the origin (home address) and destination (place of employment) for each individual in the sample who travelled to work within the town, and using the speed limits of the roads on the routes. The use of speed limits to approximate actual travel speeds should be adequate for Livingston given the efficiency of the transport system and the free flow of traffic through the town. For the bus mode Eastern Scottish timetables were used to compute in-vehicle travel times, using the fastest service if a choice existed. No journeys required transfers between services. In the case of walking, the distances were measured for the shortest route between origin and destination with a walk speed of 3.4 mph assumed to compute the travel times. These routes almost always followed the extensive footpath system in the town.

Excess travel time for walking is clearly zero, for car it was assumed zero as most cars can be parked close to the individuals house and the vast majority of workplaces had adequate parking facilities nearby. For the bus mode, however, one might expect that excess travel time would be of importance, given the generally small travel times involved.

Thus, the shortest distance to and from bus stops at the origins and destinations were measured and bus walk time computed. Given the arguments against considering wait time, in the previous study, no estimates were made of this component of excess travel time.

Car costs were estimated in the same way as in the previous study, bus costs were taken from fare schedules and walk costs were assumed zero. Given the performance of the various car cost measures in the previous study, only the marginal (out of pocket) costs were considered. Similarly, the same problems were encountered for car passengers.

Observations for which, due to close proximity, walk was the only feasible mode of travel were dropped from the sample. It could be argued that they could simply have been assigned a probability of 1, for walk, but given the small number, in the interests of simplicity they were excluded.

For the multi-nomial logit, the variables can be considered to simply enter as absolute values, their relation to those of the other alternatives being formalised within the model. Hence, there is no necessity to consider the different forms of the variables as in the binary study, for they are by implication differences.

Table 7.1 shows the results for the model containing only the time and cost generic variables and mode specific dummy variables for car and bus. Walk is the base mode and is the excluded mode specific dummy. Before analysing the results, it is worthwhile considering the implications of the variable forms.

The mode specific constants which take the value of one for the stated mode and zero for others, represent the effect of variables which influence mode choice but have not been explicitly included. If the variables included in the representative utility functions for each mode completely explained the choice of mode then one would expect the constants to be zero. Without perfect model specification and perfect data, however, it is necessary to include such constants to pick up

LEVEL OF SERVICE

TABLE 7.1

	TOTAL SAMPLE		CAR AVAILABLE		HEADS SAMPLE	
		BWT		BWT		BWT
TIME	-0.001	-0.002	-0.006	-0.007	0.005	0.003
	(-0.074)	(-0.228)	(-0.479)	(-0.518)	(0.405)	(0.289)
COST	-0.053	-0.056	-0.107	-0.109	-0.017	-0.019
	(-1.354)	(-1.417)	(-2.069)	(-2.086)	(-0.345)	(-0.390)
CAR DUMMY	0.402	0.390	1.230	1.228	0.663	0.651
	(1.766)	(1.708)	(4.109)	(4.099)	(2.328)	(2.275)
BUS DUMMY	-1.054	-0.057	-0.824	-0.419	-1.395	0.224
	(-3.198)	(-0.096)	(-1.810)	(-0.531)	(-3.105)	(0.257)
BUS SPECIFIC		-0.129		-0.048		-0.225
		(-1.867)		(-0.602)		(-1.934)
LLR	94.138	98.544	109.369	109.801	82.985	87.870
PSQ	0.147	0.154	0.255	0.256	0.205	0.217
APSQ	0.141	0.147	0.248	0.247	0.197	0.207

effects which are specific to the mode, many of which (eg comfort and convenience) are non-quantifiable. The implication of the form of such constants is thus that a negative coefficient, for example, would indicate that when the rest of the representative utility functions for the 3 alternatives are equal, an individual would still tend to choose one of the other alternatives over that which is inherent in the mode specific constant.

Related to the use of alternative specific dummies, is the use of alternative specific socioeconomic variables. It was shown in Chapter 4 that it is necessary to introduce such variables in a mode specific form. Thus, they enter in a similar manner to the constants except they take the value of the variable e.g. social class, rather than simply a constant value of 1. They can be considered to show pure mode effects which vary with the variable considered. Thus, for example, if the other components of the representative utility function for each mode are the same an individual will still choose a specific mode, but his/her choice will be related to the value of the socioeconomic variable (i.e. the social class of the individual).

In the model, there are 3 alternatives - car, bus and walk, thus only a maximum of 2 mode specific constants, or coefficients of mode specific variables can be identified. If mode specific constants or variables appear in the utility of more than one mode, then they must be interpreted, not through the absolute value of their coefficients, but rather their value relative to the other modes (which relate through the base mode). In this case, the walk mode is used as the base mode alternative and so the coefficients of the mode specific variables must be interpreted relative to it.

To assess the results, requires some a priori expectations. The strongest of these is, as regards the signs of the coefficient estimates. An increase in time or cost relating to a particular mode would be expected to lead to a decrease in the probability of choosing that particular mode. Thus, the a priori expected sign for these variables is negative. The results in Table 7.1 conform to these expectations for all

except the coefficient on the time variable for the heads sample, which is positive. The time variables for all samples are , however, insignificant, the car available sample being the only one with a significant cost variable and having the most significant time variable.

Clearly, it is difficult to judge the implications of these results, however, a few observations can be made. The car available sample appears to show the greatest sensitivity to both time and cost factors. In addition, all of the samples appear to have more significant cost that time sensitivity (excepting the heads sample which has the wrong sign for time). Considering the mode specific dummies, all are fairly significant but with relative effects which differ across the samples, although the signs are consistent. This consistency of the signs implies that for all of the samples if the utility functions had the same value (cost and time) for each mode there would be a bias toward taking car relative to walk and a bias away from bus relative to walk, implying a ranking of alternatives of car, walk, bus; which is the same as that implied by the observed proportions. Thus, there are some mode specific influences on choice, decreasing the share of bus and increasing that of car (relative to walk) which are not inherent within the sample time and cost specification.

For the total and heads samples, the most significant relative effect is the negative bus dummy coefficient, while for the car available sample, it is the positive car dummy (both in significance and magnitude). It could be surmised that this implies that those individuals who have a car available are more sensitive to the specific characteristics of that mode, such as comfort and convenience, than in the other 2 samples and being used to vehicular travel, weight the deficiencies of the bus mode less, relative to walk. As regards goodness of fit, the models all perform well, with the car available sample the best, as is expected given the greater homogeneity of this sample. Clearly problems in judgement are caused by the wrong sign of the time coefficient for the heads sample and the implied inadequacy of specification but this changes in the final model.

There are some interesting implications of these results. Firstly, despite the shortness of journeys, out of pocket costs do appear to have a relatively significant effect, a finding which is at variance with Dutch studies by DeDonnea (1971) and Richards and Ben Akiva (1975). Secondly, time is generally insignificant and the wrong sign in the heads sample, which could be the result of the time differences being smaller than usual, in such studies, and the walk mode efficient because of the extensive footpath system.

As mentioned, the only measurable component of excess travel time was bus walk time, at destination and origin. This was entered as a bus mode specific variable, but given that walk excess time is zero, this form is equivalent to a generic variable. The estimation results show the addition of BWT to have improved upon the base mode (at 5%) for both the total and heads sample, but not for the car available sample, it also has fairly significant coefficient estimates in both of these samples and has the correct sign for all.

Noticeably, the addition of BWT affects, significantly, only the bus mode specific constant reducing both its significance and coefficient magnitude. This would seem to imply, certainly for the total and heads sample, that BWT is an important mode specific component of utility. This accords with a priori expectations as clearly the amount of walking required will affect the convenience and comfort, of the mode. If a high BWT is encountered it might be worthwhile just walking to work rather than being subject to the service delays, etc., of the bus mode. That the addition of BWT for the car available sample is not significant, reflects the lower significance of the bus dummy in the base model. The same effect is observed but it is not significant. Bus walk time is weighted more heavily than in-vehicle, though less so for those with a car available. Absolute values are, however, not very high if compared with other studies; they are high relative to in-vehicle travel time in this study.

Of the other level of service variables that could have been considered none were relevant to the study. There was no necessity for transfers

and there was no apparent constraint on parking at the destinations. Further, it was not considered worthwhile to pursue the estimation of bus wait time. It was probably service delay which is the most important component of the wait time and this was not estimable, nor was wait time reported. Assuming random arrival would not be accurate and headway was generally small.

7.2 SOCIOECONOMIC VARIABLES

Socioeconomic variables have to enter the model as alternative specific variables taking the value of the variable for the relevant mode and zero otherwise. In other words, they represent interactive variables in the sense of being a composite of the socioeconomic and a mode specific dummy.

The available variable forms have already been considered in the previous study, Chapter 6. Clearly, the discussion undertaken and the conclusions reached have relevance here. On that basis the following variables are of interest:

NCR - the number of cars owned by, or available to the household

NCR1 - the number of cars per household member

NCR2 - the number of cars per full time employed household member

DSOC - social class dummy taking the value 1 if white collar worker; 0 otherwise

DSOC1 - social class dummy taking value 1 if professional; 0 otherwise

DSEC - socioeconomic group dummy taking value 1 if first four groups; 0 otherwise

DST - status dummy taking value 1 if head of household; 0 otherwise

DSAE - sex and employment status dummy taking value 1 if male full-time employed; 0 otherwise

DOCC - occupation dummy taking value 1 if administration, management or professional; 0 otherwise.

A more extensive explanation of these variables and their interpretation is presented in Chapter 6.

It is important to remember that the variables presented here are proxies for various effects on mode choice, thus it is necessary to consider which variables best represent these effects empirically. The theory and a priori reasoning provides a basis for including variables to represent the socioeconomic effects but gives no guidance for the practical forms in which they enter the models. Thus, models are estimated containing the relevant variable and compared with the "base" model, containing only the level of service variables and mode specific constants, using the likelihood ratio test. On this basis, and the level of significance of the individual parameter estimates, the performance of the variables is assessed and used as criteria for selection of variables for the final model forms. Although one could argue that if there is some a priori belief that a variable should be in the model it should be retained even if insignificant, in this case we are dealing with proxies of the hypothetical effects so if the variables do not achieve significance they do not adequately represent these effects and so should be dropped.

Table 7.2 gives the estimation results for the car available variables, entered as car specific for the three samples. For the total and heads sample, the introduction of the variables is highly significant (when compared with the base model) and for the car available sample just significant at 5%, the same pattern emerges for the significance of the individual car availability parameter estimates. The variables all have the expected positive sign, implying the larger the number of cars available for use within a household, the more likely the individuals will travel by car.

For the total sample NCR2, the number of cars per full time employed household member, would appear to perform best, while for the car available and heads sample, it is NCR1, the number of cars per household member. In actual fact, NCR, the number of cars available to the household performs marginally better than NCR1 for the heads

CAR AVAILABILITY

TABLE 7.2

	TOTAL SAMPLE			CAR AVAILABLE SAMPLE			HEADS SAMPLE		
	NCR	NCR1	NCR2	NCR	NCR1	NCR2	NCR	NCR1	NCR2
TIME	0.001	-0.001	-0.003	-0.006	-0.007	-0.007	0.010	0.005	0.002
	(0.048)	(-0.110)	(-0.283)	(-0.478)	(-0.525)	(-0.579)	(0.818)	(0.441)	(0.154)
COST	-0.065	-0.074	-0.048	-0.109	-0.121	-0.106	-0.013	-0.027	-0.007
	(-1.582)	(-1.781)	(-1.163)	(-2.090)	(-2.308)	(-2.039)	(-0.236)	(-0.498)	(-0.139)
CAR DUMMY	-0.436	-0.460	-0.707	1.144	0.681	0.616	-0.656	-0.452	-0.583
	(-1.506)	(-1.647)	(-2.355)	(2.854)	(1.681)	(1.289)	(-1.668)	(-1.235)	(-1.543)
BUS DUMMY	-0.923	-0.874	-1.140	-0.808	-0.718	-0.866	-1.337	-1.297	-1.526
	(-2.706)	(-2.539)	(-3.320)	(-1.764)	(-1.556)	(-1.868)	(-2.747)	(-2.680)	(-3.182)
CAR SPECIFIC	1.222	4.254	2.033	0.084	1.796	0.765	2.054	5.905	2.230
	(5.280)	(6.060)	(6.330)	(0.321)	(2.051)	(1.745)	(5.951)	(5.559)	(5.656)
LLR	130.854	143.195	144.660	109.472	114.586	113.826	130.056	128.933	124.473
PSQ	0.205	0.224	0.226	0.256	0.267	0.266	0.322	0.319	0.308
APSQ	0.198	0.217	0.220	0.246	0.258	0.256	0.312	0.310	0.298

OBSERVED PROPORTIONS

CAR	0.467	0.615	0.571
BUS	0.096	0.062	0.071
WALK	0.436	0.323	0.359

sample. This might be considered to imply the priority of heads of households in car use. Thus, the relevance to the head is the absolute number of cars and the other uses to which the car can be put, such as shopping or school trips by the wife, rather than competing with other household members for the journey to work, reflected further in the superiority of both NCR and NCR1 over NCR2. However, NCR suffers in not having the same interpretive value of NCR1 and NCR2 as constraint on car use and for this reason NCR1 is preferred.

Generally when compared to the base model the introduction of the car available variables has reduced the coefficient on the car dummy, but otherwise had little effect on the other model coefficients. Clearly the variables are picking up the positive bias towards car which is caused by the availability of a car for use, the effects on the car available sample being much less marked as one would expect.

The results for the household socio-economic variables, introduced as car specific are shown in Table 7.3. All variables have expected signs. For the total sample only the model containing DSEC does not differ significantly at 5%, from the base model, DSOC the variable reflecting the white/blue collar distinction being more significant that DSOC1 which represents the professional/non-professional distinction. In contrast, none of the models for the car available sample are significantly different, nor are the coefficient estimates. DSOC1 does, however, perform better than the others. This is not surprising when compared to the total sample result, as the car available sample would tend to be made up of higher social classes. For the heads sample, the only significant model is that containing DSOC which has the only significant coefficient estimate. This would seem to imply that the head of household sample is of similar composition to the total sample, and the white collar/blue collar distinction has greater effect on mode choice. That this should be the case is evident from the fact that the household socioeconomic groupings are based upon the head of the household.

These results seem to imply that the only significant effect of such social classification occurs in respect to car ownership, which is related

HOUSEHOLD SOCIOECONOMIC CHARACTERISTICS

TABLE 7.3

	TOTAL SAMPLE			CAR AVAILABLE SAMPLE			HEADS SAMPLE		
	DSOC	DSOC1	DSEC	DSOC	DSOC1	DSEC	DSOC	DSOC1	DSEC
TIME	-0.002	0.0001	-0.001	-0.007	-0.005	-0.007	0.002	0.004	0.004
	(-0.222)	(0.011)	(-0.101)	(-0.527)	(-0.409)	(-0.515)	(0.174)	(0.396)	(0.361)
COST	-0.058	-0.051	-0.053	-0.110	-0.106	-0.108	-0.022	-0.015	-0.014
	(-1.472)	(-1.305)	(-1.352)	(-2.106)	(-2.058)	(-2.086)	(-0.445)	(-0.300)	(-0.284)
CAR DUMMY	0.225	0.335	0.299	1.156	1.189	1.162	0.146	0.605	0.543
	(0.934)	(1.456)	(1.270)	(3.628)	(3.939)	(3.734)	(1.369)	(2.078)	(1.815)
BUS DUMMY	-1.035	-1.054	-1.058	-0.816	-0.818	-0.824	-1.398	-1.415	-1.428
	(-3.121)	(-3.194)	(-3.196)	(-1.789)	(-1.794)	(-1.806)	(-3.083)	(-3.144)	(-3.162)
CAR SPECIFIC	0.598	0.904	0.519	0.210	0.528	0.285	0.875	0.523	0.525
	(2.286)	(1.996)	(1.698)	(0.668)	(1.020)	(0.786)	(2.424)	(0.929)	(1.302)
LLR	99.425	98.370	97.053	109.818	110.464	109.997	89.223	88.890	84.741
PSQ	0.155	0.154	0.152	0.256	0.258	0.257	0.221	0.207	0.210
APSQ	0.148	0.147	0.144	0.247	0.248	0.247	0.210	0.197	0.199

to whether the individual household head is a white collar or blue collar worker. There is some effect based on whether professional or not, when the availability of a car is accounted for, but this is not significant.

Table 7.4 shows the estimation results for the individual socioeconomic variables entered as car specific, for the three samples. All of the models show expected signs for the coefficient estimates with DST obviously not relevant for the heads sample. For the total sample, all are significant both in terms of difference from the base model and individual coefficient estimates. DST and DSAE behave similarly and better than DOCC with DST performing marginally better. The similarity of DST and DSAE probably reflects the large proportion of male full time employed heads of households, although the significance of this variable for the heads sample implies that there is some effect based on the sex and employment status of the heads. The car available sample results differ from those of the total sample in that the occupation dummy is not significant and DST outperforms DSAE to a greater extent. DSAE as mentioned, is significant for the heads sample which DOCC again fails to achieve significance.

It would appear that DST provides the best proxy for individual characteristic effects for the total and car available sample, while DSAE illustrates that whether or not the head of household is male, full time employed or not, will have an effect on choice of mode, once the head/not head distinction has been accounted for. DSF is shown in Table 7.5 to be insignificant for all of the samples. This result is not surprising given the efficient flow of traffic within the town, even at peak time, and the relatively short journey length.

Having introduced the socioeconomic variables as car specific, the same variables were introduced as bus specific to consider whether the effects implied by the variables were better represented as bus rather than car specific. Further estimates of models with each variable entered as both car specific and bus specific were made to assess whether there was any increase in explanatory power of the model by

INDIVIDUAL SOCIOECONOMIC CHARACTERISTICS TABLE 7.4

	TOTAL SAMPLE			CAR AVAILABLE SAMPLE			HEADS SAMPLE		
	DST	DSAE	DOCC	DST	DSAE	DOCC	DST	DSAE	DOCC
TIME	0.001	-0.001	-0.002	-0.003	-0.005	-0.007		0.004	0.003
	(0.063)	(-0.100)	(-0.184)	(-0.245)	(-0.389)	(-0.535)		(0.360)	(0.269)
COST	-0.026	-0.036	-0.052	-0.060	-0.070	-0.106		-0.022	-0.017
	(-0.659)	(-0.913)	(-1.328)	(-1.076)	(-1.263)	(-2.045)		(-0.440)	(-0.340)
CAR DUMMY	-0.481	-0.417	0.251	0.002	0.098	1.114		-0.310	0.510
	(-1.544)	(-1.380)	(1.058)	(0.005)	(0.253)	(3.550)		(-0.564)	(1.706)
BUS DUMMY	-1.262	-1.203	-1.080	-1.184	-1.126	-0.849		-1.362	-1.424
	(-3.729)	(-3.566)	(-3.259)	(-2.471)	(-2.354)	(-1.857)		(-3.019)	(-3.155)
CAR SPECIFIC	1.1366	1.110	0.738	1.660	1.568	0.458		1.100	0.691
	(4.303)	(4.288)	(2.261)	(5.021)	(4.810)	(1.188)		(2.091)	(1.675)
LLR	113.691	113.473	99.409	136.227	133.832	110.830		87.655	85.949
PSQ	0.178	0.177	0.155	0.318	0.312	0.259		0.217	0.213
APSQ	0.171	0.170	0.148	0.309	0.303	0.249		0.206	0.202

START AND FINISH DUMMY

TABLE 7.5

	TOTAL SAMPLE	CAR AVAILABLE	HEADS SAMPLE
	DSF	DSF	DSF
TIME	-0.0001 (-0.011)	-0.005 (-0.368)	0.003 (0.292)
COST	-0.049 (-1.257)	-0.099 (-1.904)	-0.022 (-0.444)
CAR DUMMY	0.418 (1.799)	1.276 (4.150)	0.599 (2.057)
BUS DUMMY	-1.065 (-3.214)	-0.851 (-1.858)	-1.375 (-3.054)
CAR SPECIFIC	-0.070 (-0.253)	-0.189 (-0.563)	0.477 (1.079)
LLR	93.549	109.455	84.190
PSQ	0.147	0.257	0.208
APSQ	0.139	0.247	0.197

considering both alternative specific effects. The log-likelihood ratio values for these estimates are shown in Table 7.6 for the three samples.

Assessing the relative performance of the models on the basis of the log likelihood test, it can be seen that generally all variables perform better as car specific, excepting DSF which is anyway not significantly different from the base model, either as car or bus specific. Further, comparing the models with just car specific variables with those containing both car and bus specific, shows that except for NCR in the heads sample, none of the models differ significantly at the 5% level. These results imply that it is adequate to enter the relevant socioeconomic variables as car specific.

7.3 FINAL MODEL FORMS

On the basis of the previous analysis, the final model forms decided upon included in addition to in-vehicle time, cost, and car and bus specific dummies.

1. For the total sample: BWT, NCR2, DSOC, DST
2. For the car available sample: BWT, NCR1, DST
3. For the heads sample: BWT, NCR1, DSOC, DSAE.

Despite not being significant for the car available sample, BWT was retained in the final model as it represents a specific component of travel time about which there is a priori reasoning to suggest it should be important. Indeed, when it was excluded, although the resulting model did not differ significantly, the effect was to compensate for the lack of the bus specific component for BWT by increasing the bus specific dummies magnitude and significance. Thus, it was considered worthwhile to retain the variable. DSOC in contrast is a proxy to represent hypothetical income and social status effects and hence its insignificance leads to criticism of its role within the models. Excluding DSOC had little effect both on the models likelihood and the individual parameter estimates, implying that it does not improve the specification of the model provided by other explanatory variables. For

MODEL COMPARISONS: LLR

TABLE 7.6

	TOTAL SAMPLE			CAR AVAILABLE SAMPLE			HEADS SAMPLE		
BASE MODEL	94.138			109.369			82.985		
	BUS+CAR	CAR	BUS	BUS+CAR	CAR	BUS	BUS+CAR	CAR	BUS
NCR	133.047	130.854	104.077		109.472		134.387	130.056	98.528
NCR1	143.199	143.195	98.670	115.644	114.586	109.382	128.934	128.933	87.553
NCR2	146.020	144.660	104.503	114.920	113.826	110.866	126.777	124.473	94.086
DSOC	99.435	99.425	94.537	109.826	109.818	109.461	90.551	89.223	86.418
DSOC1	98.548	98.370	95.206	110.468	110.464	109.456		83.890	
DSEC	97.237	97.053	94.161	110.136	109.997	109.375	85.370	84.741	84.340
DST	114.055	113.691	97.820	139.378	136.227	120.242			
DOCC	100.229	99.409	96.582	111.636	110.830	110.888	86.376	85.949	84.333
DSF	94.262	93.549	94.261	110.267	109.455	110.214	84.395	84.190	82.988

these reasons, it was excluded in the final model, the results of which are given, for all three samples, in Table 7.7.

On the basis of these results, it is clear that the probability of choosing a given mode is largely determined by factors other than the time and cost, level of service, of that mode, although walk time required to use the bus mode is generally a significant deterrent for the use of that mode. Both time and cost are insignificant for all three samples, with the car available sample giving the largest weighting to both of thoese components. Excess travel time in the form of bus walk time is however, most highly weighted by the heads, followed by the total sample, and insignificant for the car available sample.

For the total and heads sample, the car specific dummy variable achieves significance, implying the existence of car specific efects not reflected in the other explanatory variables. However, the negative sign implies bias against the car mode, a reversal of the sign on the car specific dummy when only the level of service variables were considered. Thus, the specification of the model has explained the car specific effects which make it preferable relative to walk, but there are clearly features reflected in the constant which imply a bias away from car relative to walk. (**NB:** the previous ranking and interpretation on the basis of the mode specific constants is not possible here because of the existence of other car specific variables).

None of the samples have bus specific constants significant, as a result of the introduction of bus specific bus walk time. It was seen that BWT picks up a large proportion of the bias against bus relative to walk, indeed for the heads sample, the sign of the constant changed from negative for just level of service to positve with the introduction of BWT. This might be considered to imply that the argument for not considering wait time, given the practical difficulties were justified.

All of the car specific socioeconomic variables are significant and positively signed, indicating their importance in influencing the choice of mode. Rather than mode choice being influenced by time and cost it

FINAL MODEL FORMS

TABLE 7.7

	TOTAL SAMPLE	CAR AVAILABLE	HEADS SAMPLE
TIME	-0.003 (-0.309)	-0.005 (-0.383)	0.003 (0.279)
COST	-0.023 (-0.553)	-0.074 (-1.304)	-0.036 (-0.651)
CAR DUMMY	-1.540 (-4.026)	-0.699 (-1.294)	-1.774 (-2.428)
BUS DUMMY	-0.228 (-0.366)	-0.570 (-0.686)	0.511 (0.550)
BWT	-0.146 (-2.015)	-0.062 (-0.743)	-0.245 (-1.976)
NCR1		2.118 (2.058)	5.923 (5.580)
NCR2	2.012 (6.125)		
DST	1.069 (3.761)	1.695 (4.998)	
DSAE			1.456 (2.173)
LLR	164.335	142.036	139.545
PSQ	0.257	0.332	0.345
APSQ	0.248	0.319	0.332

would appear to depend upon the constraint on car use, as represented by NCR1 and NCR2, and the status of the individual within the household, as represented by DST and DSAE. For the total sample, the number of cars available per full time employed member of the household and whether the individual is the head of household or not, are the relevant variables. When the car mode choice is considered as exogenous, in the car available sample, the number of cars per person in the household, still implies that the constraint on car use, and the head/not head dichotomy is important. That NCR1 is used rather than NCR2 might seem to have implications for the allocation of car use, clearly the head has priority but the constraint is determined by the number of cars relative to household size which might mean it is the possible other uses for the car, (eg. shopping, driving kids to school) rather than the competition for use between full time employed household members, that is most relevant.

When only the heads of households are considered DSAE, taking the value 1 for male full time employed; 0 otherwise, is relevant and significant. This implies that once the head/not head distinction is accounted for, whether or not the head of household is male and in full time employment still has a significant effect upon mode choice. Again, as with the car available sample, NCR1 is of relevance and significant with similar implications for the allocation of car usage, relative to walk.

The exclusion of the social class variables with their intended proxies for social environment and income is unfortunate, given that simply because the proxy failed does not mean the effects are insignificant. However, the general good performance of the models with such might be considered to imply that in the study the individual characteristics and car availability are of more importance, or that car availability reflects adequately social class distinctions.

7.4 COMPARISON WITH THE JOURNEY TO EDINBURGH

Having analysed the determinants of mode choice for the journey to

work within Livingston, it should be instructive to compare the results with those obtained for the journey to work in Edinburgh. Although Edinburgh was only one of the destinations for out commuters and so not really representative of all work journeys out of Livingston, it was, by far, the most important taking about 35% of out commuters. In addition, the comparison of a study of commuting within a New Town and commuting between a New Town and its nearest large city neighbour provides useful information on travel in the New Town context.

Before considering the empirical results of the analyses, it is worthwhile contrasting the characteristics of the journeys, both in terms of the journeys themselves and the commuters who undertake them. The journey to work within Livingston reflects the features of New Town developments in terms of minimised and efficient work journeys with walking being an important alternative to car and bus [1]. Further, both car and bus have the benefit of efficient road networks, with bus walk times minimised by the location of bus stops within 400 metres of dwellings. For the journey to work in Edinburgh, these features are relevant only at the origin, the commuter facing a journey of about 14 miles (on a less efficient road system) and the destination characteristics of Livingston, which can require bus transfers and possibly parking difficulties. As was seen in Chapter 5, there are deficiencies, caused by practical limitations in the representation of these destination characteristics. Their effects, however, should be manifest, at least to some extent, in the empirical results.

As regards the commuters, Appendix 7 outlines the differences in terms of socioeconomic features between those households containing workers

1. **Indeed, as shown in Table 7.2 car and walk accounted for around 90% of observed mode choices.**

commute to Edinburgh, and the total sample. This shows the households with at least one worker in Edinburgh to be concentrated in the higher social class and socioeconomic groups, with related lower unemployment, smaller household size and a much higher level of car ownership. In addition, the characteristics of the individual commuters showed them to be predominantly in professional and service employment. This feature reflects the importance of Livingston within its regional context and the importance of Edinburgh in providing the professional and service employment lacking in Livingston with its characteristic New Town bias towards manufacturing employment.

In comparing the results of the empirical studies the different specifications of the model make comparisons based upon relative coefficient values somewhat tentative. Further, the model results for the heads sample of the journey to work within Livingston give an incorrect sign for the time difference variable. This clearly detracts from the interpretive value of any comparison of the models estimated on this sample. In addition, the models differ in the alternatives considered. The within Livingston model had 3 alternatives car bus and walk with walk as the base mode. Thus all alternative specific coefficient estimates are relative to the base mode, walk, and clearly not directly comparable with the binary Edinburgh-Livingston model which considered only car and bus. The differences in specification do, however, in terms of their selection of the candidate explanatory variables, shed light upon the differences between the two studies.

As regards the car availability variables NCR2, the number of cars per full time employed household member, performed best for the Livingston-Edinburgh study, while excepting the total sample, NCR1, the number of cars per household worker, performed best for the within Livingston study. It might be expected that for the longer journey the relevant car constraint would be reflected in the claims of the employed household members. For the shorter within Livingston journey, however, the claims of other household members might become more relevant with, for example, housewives having a more forceful claim for the use of the car for shopping or taking the children to

school. This reasoning would be consistent with the results obtained were it not for the inclusion of NCR2 in the total sample model for the within Livingston journey.

For the within Livingston study none of the variables reflecting household social status were selected, while for the Edinburgh-Livingston study DSOC1, reflecting a professional/non professional effect, was significant for the total and car available sample. This would appear to reflect the nature of commuters to Edinburgh. The vast majority are either professional or service workers and the professional workers appear to be more likely to travel by car, The variable was not important for the heads sample because of the predominance of professional workers in the sample. Further DSOC1 would not be expected to be of relevance for the within Edinburgh journey because of all the bias of the towns employment towards manufacturing, although the failure of DSOC the white/blue collar dummy can only be explained by its failure as an income/social status proxy.

The effect of the status of the individual within the household was best represented by DST for the total and car available samples in both studies, while DSAE was found to be significant only for the heads sample in the within Livingston study. DST takes the value of 1 for individuals who are heads of households and 0 otherwise. Thus, it would appear that whether or not the individual was head of their household was an important determinant of mode choice in both studies. This seems to represent the priority of the head of the household in determining car use.

The start and finish time dummy was only found to be relevant for the Edinburgh-Livingston journey. Thus, whether or not the individuals travelled at peak periods or not did not appear to effect choice of mode for the journey within Livingston. This is an expected finding given the short journeys and efficient road system within Livingston as compared with the problems of the journey to Edinburgh.

Turning to the level of services variables, time and cost are both less heavily weighted (in terms of coefficient magnitude) and less significant for the within Livingston study. The difference is, however, fairly marginal for the car available sample and the coefficient for the heads sample is the wrong sign. As mentioned, this failure of the time coefficient to meet with a priori expectations clearly causes problems in comparing the heads sample models as does the generally low significance of many of the level of service parameter estimates. For both models the cost variables are more significant than the time variables.

Overall, for both journeys the choice of a particular mode would appear to be determined mainly by factors other than the levels of service of the alternative modes. Although the time and cost variables are, as would be expected, more important for the longer journey. These findings clearly have important implications for transport planning in New Towns and will be considered in more detail in Chapter 10.

CHAPTER 8

AGGREGATION AND PREDICTION

8.0 INTRODUCTION

The benefits of disaggregate behavioural models over the traditionally used aggregate models have already been established for the analysis of the determinants of travel choice. A crucial consideration, as regards the usefulness of such models is, however, their ability to make the predictions required by policy makers. Often in policy analysis, it is necessary to consider the effects of various policies on demand at a level of aggregation relevant to the alternatives being studied, hence as aggregate models relate to movements of groups rather than individuals, they will be closer to the unit of prediction than their disaggregate counterparts. It is therefore necessary to determine methods by which disaggregate models can be utilised in the formation of aggregate predictions.

This task is undertaken in this chapter. The first section outlines the relationship between disaggregate models and aggregate predictions and section two presents the groupings of the available aggregation procedures. These procedures are then presented analytically in sections three to seven. Section three presents the naive approach; section four the enumeration approach, section five the statistical differentials approach; section six the density function approach and section seven the classification approach. The choice of aggregation procedure for predictive purposes is seen to be mainly an empirical question and so section eight presents the results of the empirical application of the various methods to the Edinburgh - Livingston mode choice study.

For the analysis presented in this chapter, the focus is the binary choice model used for the Edinburgh - Livingston study. The various approaches are compared and assessed using the models for the total

sample and the car available sample. Thus much needed empirical evidence of the relative merits and applicability of these relatively neglected, though very important procedures, is provided.

The scope of such tasks precluded given the time and resource constraints the application of the approaches to the multinomial within the Livingston study. This is unfortunate, but the binary is better for illustrative purposes as some procedures are difficult to generalise.

8.1 AGGREGATE MODELS

In the situation were data is available on individual socioeconomic and trip characteristics, disaggregate models provide a conceptually simple approach to aggregate prediction. The expected choice behaviour can be estimated for each individual and then summed or averaged at the level of aggregation required. This, however, is not the general case and often it will be necessary to make predictions on the basis of summary data and, in general, aggregate predictions from disaggregate models will require, because of the non-linearity of the functional form, more data than their aggregate counterparts. Thus, it is worthwhile to consider whether the extra effort will be justified by the results.

The use of an aggregate model requires the estimation of aggregate choice based on the zonal average of the relevant variables. This implies the assumption that zonal averages are representative of the individuals within the zone and thus, an implicit aggregation procedure based upon the assumption of homogeneity of those individuals. To utilise a disaggregate model requires the explicit consideration of an aggregation procedure, taking into account the distribution of the individual variable values, and hence choice probabilities, across the prediction group. This can clearly be considered an advantage in the sense that the explicit aggregation procedure can be theoretically consistent; predictions can be made at any level of aggregation required and generality is implied by the assumption of homogeneity becoming a special case.

Further, in basing the aggregate predictions upon a disaggregate behavioural model, the advantages of consistent theoretical basis (in utility theory) and sensitivity to policy controllable variables are retained and taken account of by means of distributional considerations.

In contrast, aggregate models might be considered "descriptive" relating aggregate phenomenon without regard to the underlying behavioural aspects of individual behaviour and hence, deficient in their predictive capabilities. It might be possible to achieve more accurate predictions using the simpler aggregate models, possibly dependent upon the degree of change, but they would still be less capable of modelling changes in policy controllable factors influencing individual choice.

A further advantage claimed for disaggregate models used in prediction [Watson and Westin (1975)] is their flexibility of applications and spatial and temporal transferability implied by their consistent theoretical basis.

8.2 AGGREGATION PROCEDURES

Having considered the advantages of disaggregate models in making aggregate predictions, it is necessary to consider the various methods by which such predictions can be achieved. Following Koppleman (1976;1974), the various approaches can be grouped according to the method by which the distribution of explanatory variables is represented.

1. The naive approach - where the estimated model form is used together with the average values of the independent variables to estimate the average probability.

2. The enumeration approach - where the explanatory variable values are used for every number of the prediction group, or some subset.

3. The statistical differentials approach - where the distribution of the choice probability estimates are weighted by the probability density function based upon the independent variables.

4. The density function approach - where the distribution of the choice probability estimates are weighted by the probability density function, based upon the independent variables.

5. The classification approach - where members of the prediction group are assigned to classes, differentiated by choice set or selected independent variable values. The average variable values being used to predict the average probability for each class and then the overall average probability being computed as a weighted average of the class estimates.

8.3 NAIVE APPROACH

The naive approach in the simplest and possibly the most obvious approach to achieving aggregate predictions. All that is required are the average values of the independent variables and the coefficient values estimated on the basis of the disaggregate model. The averages of explanatory variables are simply substituted into the model giving for the logit:

$$E(P) = \frac{e^{\bar{x}'\beta}}{1 + e^{\bar{x}'\beta}} \qquad (8.1)$$

where

$$\bar{x}'\beta = \sum_k \beta_k \bar{x}_k$$

Though using the average values of the variables this approach does still have the advantage over the aggregate model that the underlying model and hence, the coefficient estimates are estimated at the disaggregate level. However, it implicitly assumes that each individual will behave as if represented by the average value of the variables, thus basing the analysis on the representative individual, in the Marshallian sense, and taking no account of the distribution of variable values across the population.

If the aggregate forecasting model

$$E(P) = f(\bar{x}'\beta) \tag{8.2}$$

was based upon a linear disaggregate model with the same linear specification, then it would be possible to achieve unbiased forecasts of the average probability E(P) as

$$E(\bar{P}) = f(\bar{x}'\beta) = f_t(\bar{x}'\beta) \tag{8.3}$$

where $f_t(\bar{x}'\beta)$ models the probability of choice of an individual t facing average values for all of the explanatory variables. If however, the functional form is non-linear such as in (8.1) this equality (8.3) will only be true if all individuals have identical values for the explanatory variables, or more generally the same value for $f_t(\cdot)$. Thus, the use of this procedure will, except in this limiting case, result in biased estimates of the E(P). The bias introduced by this approach is considered further on page .

The naive approach does have the advantage that it uses no more data that aggregate models yet still has an underlying disaggregate specification. It is also easy to calibrate and would be the approach most likely to be used if the aggregation problem was not recognised.

Improvements could be made to the use of the naive method by means of classification (as shall be considered) or by deriving empirically some form of bias correction based upon the average and variance of the $x'\beta$ and hence, taking into account heterogeneity.

8.4 ENUMERATION APPROACH

This approach simply considers estimation of the average probability by estimating each individual choice probability and then finding the average value. The whole of the prediction group can be considered

(complete enumeration) or some subset of that group (sample enumeration). Thus

$$E(P) = \frac{1}{N} \sum_i P_i \qquad (8.4)$$

where

$$P_i = \frac{e^{x_i'\beta}}{1+e^{x_i'\beta}}$$

Although providing the most theoretically consistent approach enumeration has rather extreme data requirements, as it would need predictions of variable values for each individual in the predictions group (or subset) with which to calibrate the model.

8.5 STATISTICAL DIFFERENTIALS APPROACH

In this approach, the expected probability is predicted on the basis of the moments of the distribution of probabilities over the population. Talvitie (1973) linearises the disaggregate choice function using a Taylor's series expansion about the mean of $x'\beta$ (i.e. $\bar{x}'\beta$) up to the second order terms, namely:

$$E(P) = E(P)\Big|_{\bar{x}'\beta} + (x'\beta - \bar{x}'\beta)\left.\frac{dE(P)}{dx'\beta}\right|_{x'\beta} + \frac{1}{2}(x'\beta - \bar{x}'\beta)^2 \left.\frac{d^2E(P)}{d(x'\beta)^2}\right|_{\bar{x}'\beta} + \ldots \qquad (8.5)$$

where $E(P)\Big|_{\bar{x}'\beta}$ is E(P) evaluated at the mean of $x'\beta$

and $x'\beta$ being the general form of the individual specific $x_i'\beta$.

This gives, for the logit [Talvitie (1973)]

$$E(P) = \bar{P} + \sigma^2 \left[\bar{P}(\bar{P}-1)(\bar{P}-\tfrac{1}{2}) \right] \qquad (8.6)$$

$$\sigma^2 = Var(x'\beta) \; ; \quad \bar{P} = \frac{e^{\bar{x}'\beta}}{1+e^{\bar{x}'\beta}}$$

This approach has limited information requirements, needing only the mean and variance of the linear combination of explanatory variables to estimate E(P). It takes into account the within zone variance (the departure from homogeneity) through its use of the distribution moments of the explanatory variables, and hence, probabilities to achieve unbiased aggregate estimates, thus making it superior to the naive approach.

There is, still some information loss arising from the zonal aggregation, implied by the use of the distribution moments, and the truncation of the expansion at the second order terms. However, in most cases, this will be a valid approximation and further the higher order terms can be unstable [Talvitie (1976)] and difficult to derive, making generalisation to multiple choice situations difficult. This would appear to imply that the suitabiity of this approach is an empirical question, dependent upon the magnitude of the higher order terms and hence, the acceptability of assuming their non-importance.

The use of the statistical differentials approach illustrates the bias that can be introduced by the naive approach as it will only be possible to get the same result from both approaches when the zonal averages are exact and the variance is zero, implying equation 8.6 becomes:

$$E(P) = \bar{P} \tag{8.7}$$

which is 8.1.

It is interesting to consider the bias implied by the use of the naive approach when there exists heterogeneity represented by the value of ^{2} within the sample. Consider equation 8.6 which implies that E(P) is equal to $\bar{P}$ only if there is zero variance, or $>\bar{P} = 1/2$.

Now if the variance is non-zero, the direction of bias of $\bar{P}$ resulting from its lack of consideration of the non-zero variance is:

1. if $\bar{P} > \frac{1}{2}$ $(\bar{P} - 1)$ is negative $(\bar{P} - \frac{1}{2})$ is positive hence if

we write (8.6) as (8.7) ie $E(\rho) = \bar{P} + \sigma^2 C$

where $C = \bar{P}\ (\bar{P} - 1)\ (\bar{P} - \frac{1}{2})$

then in this case $\bar{P}$ has a negative bias as C will be negative.

2. if $\bar{P} < \frac{1}{2}$ $(\bar{P} - 1)$ is negative, $(\bar{P} - \frac{1}{2})$ is positive, and hence, C in equation (8.7) will be positive implying that $\bar{P}$ will be biased upwards.

It is also of interest that the larger σ^2 and $\bar{P}$ (hence $\bar{x}'\beta$), the larger will be the absolute magnitude of the bias introduced by ignoring the heterogeneity of the sample. As Talvitie (1975) notes, it is therefore of interest to find out the types of ranges of the moments experienced in practice, as if σ is never greater than 1.0 the errors from using the naive prediction are less than 6% which given other possible uncertainties might be considered acceptable. Further, Talvitie (1973) puts forward an "empirically derived bias correction" for the naive:

$$E(P) = \bar{P} + \left(\frac{\sigma - 0.5}{\bar{x}'\beta} \right) (\bar{P} - 0.5)^2$$

This measure is not derived by Talvitie, being merely stated. Its usefulness will clearly depend on its empirical acceptability for the study in question as if it is greater than 0.5 the correction will be positive and, if not, negative. This can create problems as the direction of the bias corrections will tend to be in error if $\sigma > 0.5$ and $\bar{P} < 0.5$. This reasoning relates to the direction of bias of the naive implied by the use of the statistical differentials approach.

If this problem arises, of the bias correction taking the wrong sign, it might be worthwhile to reverse the sign and still use the correction, as long as it can be shown empirically to improve the naive (as it should).

8.6 DENSITY FUNCTION APPROACH

This approach attempts to represent the distribution of the variables across the population in terms of a frequency distribution. Considering

a group of individuals with known, but differing socioeconomic variables, each choosing an alternative represented by a set of known, but differing attributes. Then if the distribution of the socioeconomic variables and the attributes of the alternatives can be assumed known and distributed with relative frequency distribution F(x,s) the expected proportion of the population choosing alternative j is

$$E(P_j) = \int_x \int_s P_j \, F(x,s) \, ds \, dx \qquad (8.8)$$

It is thus possible to derive an aggregate model from a non-linear disaggregate model by integration (or summation) of the relation over the distribution of the independent variables. This will, however, produce an aggregated model which is specific to the population and the area (and the time) for which the distribution is relevant unless the prediction zones have similar distributions to that on which the model was estimated. The underlying disaggregate model, on the other hand, does not place any constraints on the distribution of the variables and hence can be aggregated over any population of interest, giving predictions sensitive to any changes in the distribution of the independent variables.

This transformation of a disaggregate non-linear model to an aggregate model may be intractable or at least require considerable effort. It is surely better however, to face this problem rather than to assume it away, as is done in the use of traditional aggregate models. At least the underlying simplifying assumptions that are needed will be made explicit especially in situations where the joint distribution is unknown and has to be assumed.

Westin (1974) simplifies this procedure by considering the formulation of a family of distributions that could be used to model the population relative frequency distribution (RFD) of probabilities [f(p)]. The aggregate prediction is then:

$$E(P) = \int_0^1 Pf(P)dP \qquad (8.9)$$

The RFD of probabilities is derived by assuming the explanatory variables, both level of service and socioeconomic to be distributed multivariate normal with mean μ_x and variance-covariance matrix Σ $X \sim N(\mu x, \Sigma)$.

This implies that the linear combination of coefficient weighted explanatory variables $x'\beta$ will be distributed normal

$$x'\beta \sim N(\beta'\mu_x, \beta'\Sigma\beta) \qquad (8.10)$$

In addition, the binary logit model implies a density function for the probabilities of:

$$f(P) = g\left[\log\left(\frac{P}{1-P}\right)\right]\left(\frac{1}{P(1-P)}\right) \qquad (8.11)$$

where g[.] is the probability denisty function. Combining this with the assumed distribution for $x'\beta$ gives:

$$f(p) = \frac{1}{\sqrt{2\pi}\sigma}\,\frac{1}{P(1-P)}\exp\left\{-\frac{1}{2\sigma^2}\left[\log\left(\frac{P}{1-P}\right)-\mu\right]^2\right\} \qquad (8.12)$$

$$0 < P < 1$$

Which defines the S_B family of distributions (probability density functions) as developed by Johnson (1949). These distributions satisfy the criteria of preservation [1], parameterisation [2], and flexibility [3] that Westin considers to be the necessary conditions for a useful distribution.

In practice, the problem of obtaining the maximum likelihood estimates of the parameters of the S_B distribution will be intractable because of the unobservable nature of the relevant choice probabilities; hence it is necessary to use an indirect estimation procedure. Namely:

1. getting consistent estimates of $\hat{\mu}_x$ and $\hat{\Sigma}$ from the observations on the explanatory variables and the estimates of $\hat{\beta}$ from the model [4].

2. estimating $\hat{\mu} = \beta\hat{\mu}_x$ and $\hat{\sigma}^2 = \hat{\beta}\hat{\Sigma}\beta$ which are consistent estimates of μ_x and $\beta'\Sigma\beta$.

1. **That the distribution be preserved under reasonable changes in the underlying characteristics.**

2. **That changes in characteristics determining individual choices can be represented by changes in the distribution moments.**

3. **That the family of distribution be large enough and flexible enough to fit most reasonable RFD's of estimated probabilities.**

4. **Requires random sampling as S_B parameters depend on both structural parameters β and unknown moments of explanatory variables x. Thus observations are required which give consistent estimates for the moments of x.**

3. characterising the fitted distribution of the individual probabilities as

$$S\ (\hat{\mu}, \hat{\sigma}^2)\ ^1$$

This will give the aggregate predictions

$$E(P) = \int_0^1 P\, f(P)\, dP \qquad (8.13)$$

where $f(p) = S_B(\hat{\mu}, \hat{\sigma}^2)$

with the distribution of characteristics and hence individual probabilities explicitly considered by weighting the probability estimates by the probability density function [2].

The simplification of assuming a multivariate normal distribution for the explanatory variables has been considered for the probit model by McFadden and Reid (1976).

The probit model:

$$P_i = \Phi(x'\beta) \qquad (8.14)$$

gives an expression for the aggregate prediction

$$E(P) = N\ \Phi\left(\frac{\beta'\mu_x}{\sqrt{1+\beta'\Sigma\beta}}\right) \qquad (8.15)$$

1. **These parameters which characterise the distribution are not the moments of the distribution. Rather the moments are a very complex form of these parameters [See Johnson (1949)].**

2. **The approach can be used with both dummy and continuous variables together or the extremes of all dummy, or all continuous.**

where Φ is the cumulative standard standard normal distribution. In this case, $\sqrt{1+\beta'\Sigma\beta}$ will reflect the heterogeneity of the individuals as

$$\beta'\Sigma\beta = 0$$

would mean that the aggregate and disaggregate models of this form would be the same.

This approach can be used, even if the model is logit, to provide approximate aggregate predictions. This stems from the similarity of the results provided by logit and probits models [1]. Indeed, Cox (1966) found, in analysing numerical utility values ($x'\beta$) that the relation between the logit and probit models was such that a utility value of 1.0 for the probit corresponded approximately to a utility value of 0.6 for the logit. However, if the distribution, formally derived from the logit, proves itself adequate, such an approximate will not be required.

Clearly the assumption of multivariate normality for the distribution of the explanatory variables, though justifiable in terms of simplicity, tractability, and often empirical verification, is not the only available one. Indeed, it might be considered that this assumption leaves the approach open to criticism unless it can be empirically verified. It is possible to consider other joint distributions or even to assume different distributions for the individual explanatory variables [2] (eg. income as pareto) though this will clearly lead to greater complications, and the distributions implied for the individual probabilities could be at least difficult to derive if not intractable.

Alternatively, it is possible to start with the actual RFD of probabilities as estimated by the model for the sample or some convenient form. This would, however, not allow the analysis of the effect of changes in the explanatory variables on the RFD of the probabilities and make the analysis specific to the sample used. It might be possible to use the true RFD to test the

1. For example see: De Donnea (1971); Domencich and McFadden (1975); Rassam et al (1971); Talvitie (1972).

2. Determined from theoretical and/or empirical analyses. One might possibly assume the components of x to be independently distributed. The simplest ie most unrealistic being where all explanatory variables are independent (no covariance term). It might then be possible to specify individual distributions.

acceptability of the predictions of the fitted distributions and the underlying assumption (such as multivariate normality) in many instances.

8.7 CLASSIFICATION APPROACH

This approach is an attempt to improve upon the naive approach by dividing the prediction group into relatively homogeneous groups of individuals, or market segments, and then estimating the average probability on the basis of the average probabilities over all of the market segments. Clearly this improves upon the naive approach making the homogeneity assumption more plausible while retaining its inherent simplicity of application. It also represents an improvement over the practice of spatial delineation as used in computing zonal values for aggregate models.

In practice, the delineation of the groups can be on the basis of the value of some explanatory variables, such as car ownership or income,[1] which have proved to be the most important, and/or choice set availability. This should , hopefully, provide homogeneity within the groups allowing efficient and more accurate use of the naive method upon the segments. The estimated average probabilities for each segment can then be averaged (and possibly weighted) to give the result pertaining to the population. Thus, the average probability will be:

$$E(P) = \frac{1}{N}\sum_i \bar{P}_i \qquad (8.16)$$

where $\bar{P}$ is the naive average probability estimate for group i

N is the number of groups N under $\bar{P}$

or

$$E(P) = \frac{\sum_i N_i \bar{P}_i}{\sum_i N_i} \qquad (8.17)$$

1. **Some authors eg. Hensher (1974) have attempted classification on the basis of non-quantifiable "psychological" variables such as comfort and convenience to improve upon the model.**

Whether or not the classifications used in practice are adequate in providing homogeneity is clearly an empirical question dependent on data availability and having a large enough sample to make the creation of subsamples meaningful. It is, however, to be expected that classification on the basis of important variables should increase homogeneity within subsamples and hence improve on the direct use of the naive approach, there is certainly evidence to support this [eg. Talvitie (1973); Koppleman (1974)].

8.8 EMPIRICAL APPLICATION

The choice of aggregation procedure for predictive purposes would appear to be largely an empirical question dependent on the particular situation and the form of the available data. It is, therefore, worthwhile to consider the results of the various procedures on the estimated models. This allows the analysis of the adequacy of the various procedures in replicating the observed results within the specific empirical situation, and a comparative assessment of their performance. Further, by considering both the final model and the simple model containing only the level of service variables it is possible to analyse the implied dependence of aggregation on the average and variance of $x'\beta$. This analysis is undertaken for the total and car available sample results obtained in the study of the journey to work in Edinburgh in Chapters 5 and 6.

In using a binary logit with a constant term, the complete enumeration approach will give an average probability which is constrained to be equal to the observed proportion of car users. Thus, the complete enumeration results can be used as a basis for comparison for the various procedures.

The results of the aggregation procedures applied to the simple, level of service variables only, model for the 3 sample are illustrated in Table 8.1. As was expected, the naive approach tends to overestimate the observed proportion, its inaccuracy increasing with the size of VARXB. In these models, however, the value of VARXB was relatively small and hence, so was the degree of bias. The empirical bias correction did improve upon the directly estimated naive, although the sign of the bias correction had to be reversed for the car available sample as σ was greater than 0.5.

Using the statistical differentials to correct for sample heterogeneity gave the observed proportion except for a small error in the car available sample, probably resulting from its higher value for VARXB.

AGGREGATION PROCEDURE RESULTS

TABLE 8.1

MODEL:	LEVEL OF SERVICE		FINAL MODEL	
SAMPLE:	TOTAL	CAR AVAILABLE	TOTAL	CAR AVAILAB
COMPLETE ENUMERATION	0.658	0.771	0.695	0.771
NAIVE	0.664	0.783	0.766	0.826
CORRECTED NAIVE	0.652	0.775	0.675	0.760
STATISTICAL DIFFERENTIALS	0.658	0.770	0.569	0.747
DENSITY FUNCTION	0.658	0.771	0.630	0.744
CORRECTED DENSITY FUNCTION			0.658	0.772
AVERAGE-AVXB	0.681	1.283	1.184	1.832
VARIANCE-VARXB	0.176	0.263	4.120	2.680

The fitted S_B distribution, as shown in Figure 8.1 also gave average probabilities very close to the observed proportion implying the distribution and its underlying assumptions are not too restrictive. Indeed, Figure 8.2 and 8.3 shows the distribution of the $x_i'\beta$s to be easily approximated by a normal distribution for the two samples while the fitted S_B distributions illustrated in Figures 8.1 and 8.4 appear to fit the estimated probabilities fairly well, closely approximating the trend implicit in the probability distribution.

The addition of the relevant explanatory variables to make up the final model forms led to a marked increase in the value of VARXB over the simple, level of service variables only, model. As expected, the results in Table 8.1 show the increase in VARXB to have increased the bias of the naive approach and the increased complexity of the model structures has generally meant that none of the procedures perform as well as previously, although they are better for the more homogeneous car available sample. The overestimation of the naive was considerably reduced by the empirical bias correction, although the sign of the correction had to be reversed. The statistical differentials approach was the least accurate possibly implying that the higher order terms of the Taylor expansion could not be assumed insignificant, for the models.

Using the more complicated models makes the task of the density function approach more difficult. The distribution of the $x_i'\beta$ is more complex and the normality assumption required for the fitted S_B less evident. Indeed, as can be seen in Figure 8.5 and 8.6, the introduction of the socioeconomic dummy variables has made the distribution of the $x_i'\beta$ somewhat bimodal in shape. As illustrated in Figure 8.7 and Figure 8.8, the unimodal S_B distribution is not a good approximation to the bimodal distribution of the estimated probabilities. There is, however, less deviation for the car available sample distribution with its smaller proportion at the lower probabilities and for both samples the fitted S_B distribution does, in fact, follow the general trend although tending to overestimate at the extremes and underestimate at the centre of the distribution. Consequently, it would appear worthwhile to consider the empirical results given by the approach.

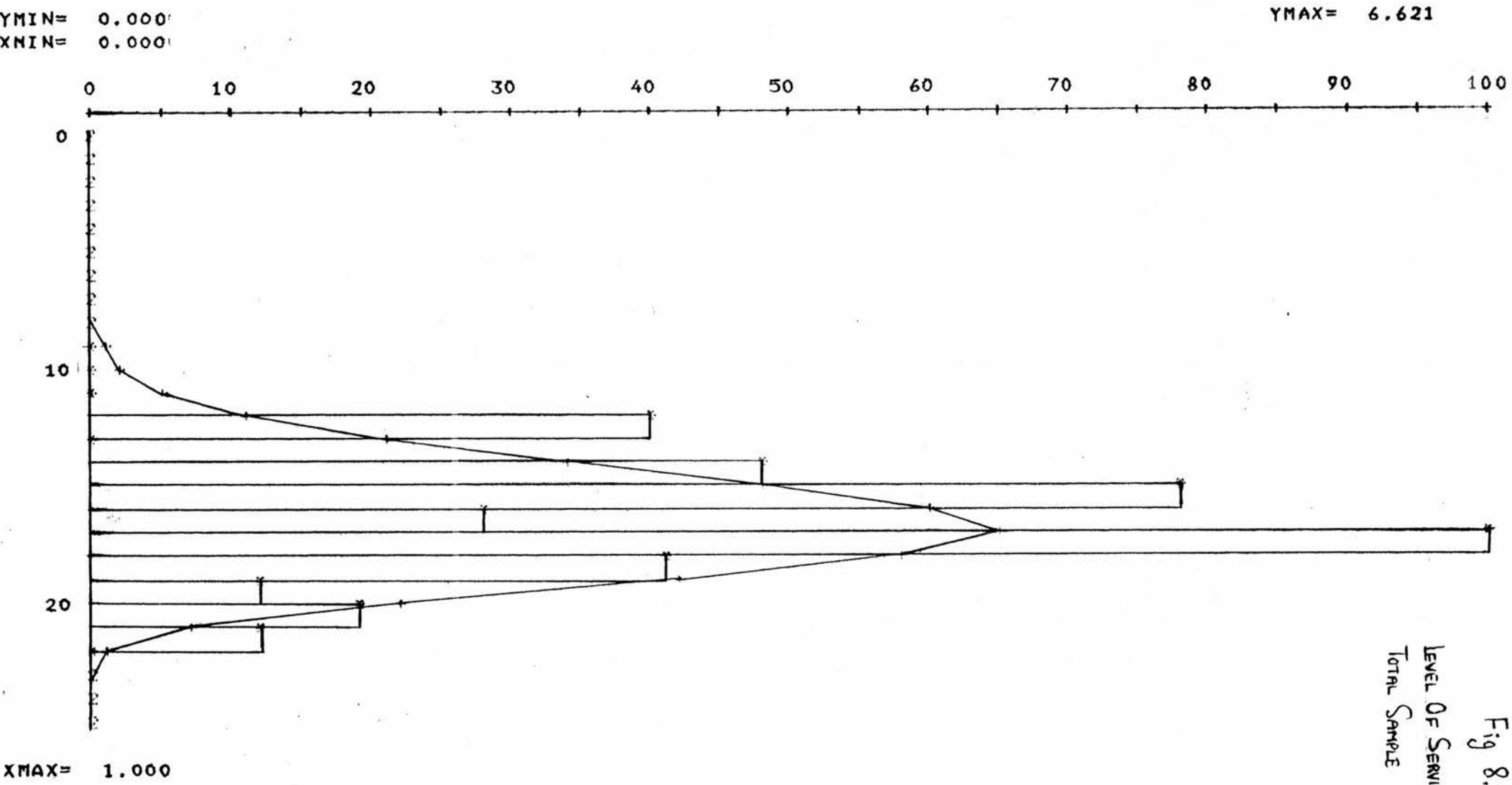


Fig 8.1
Level Of Service
Total Sample

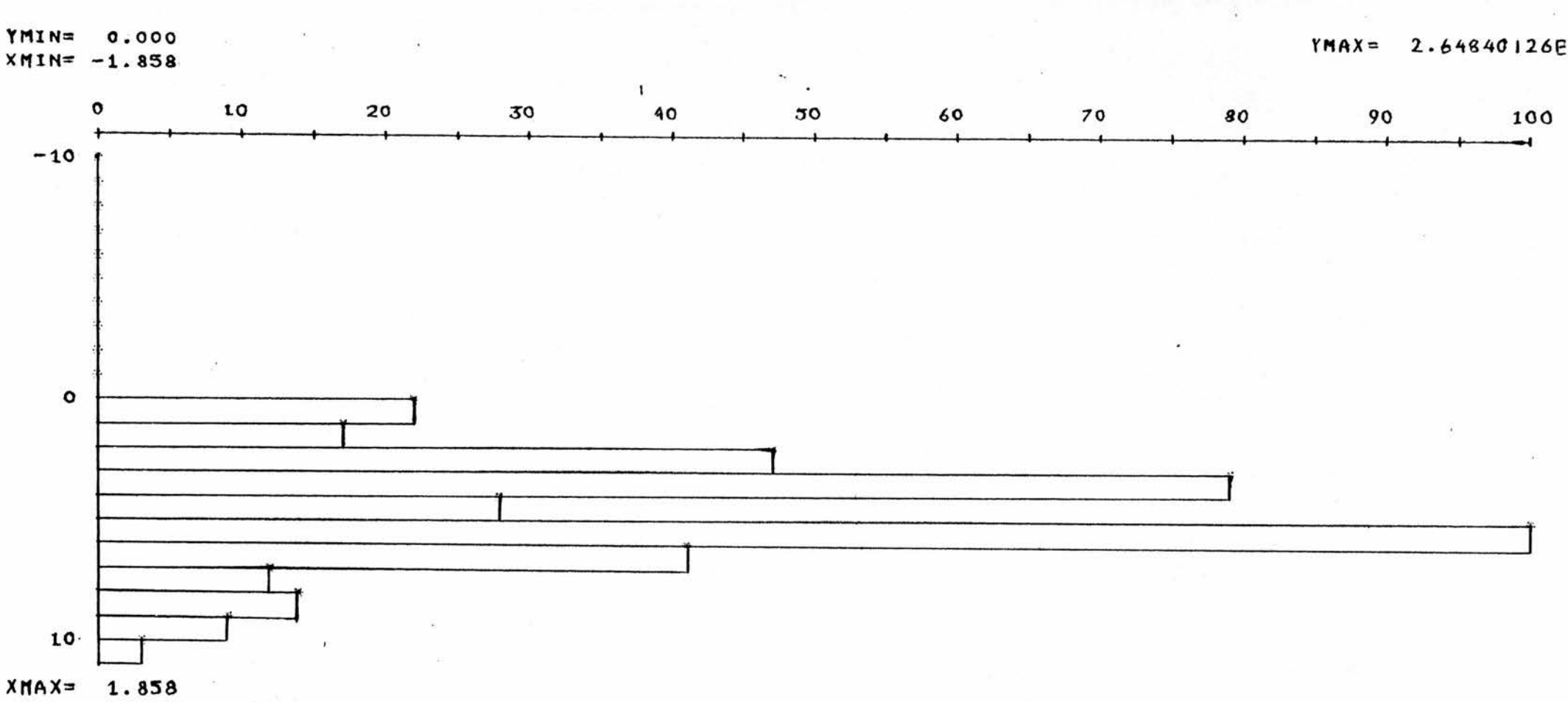


Fig 8.2
Total Sample
Level Of Service

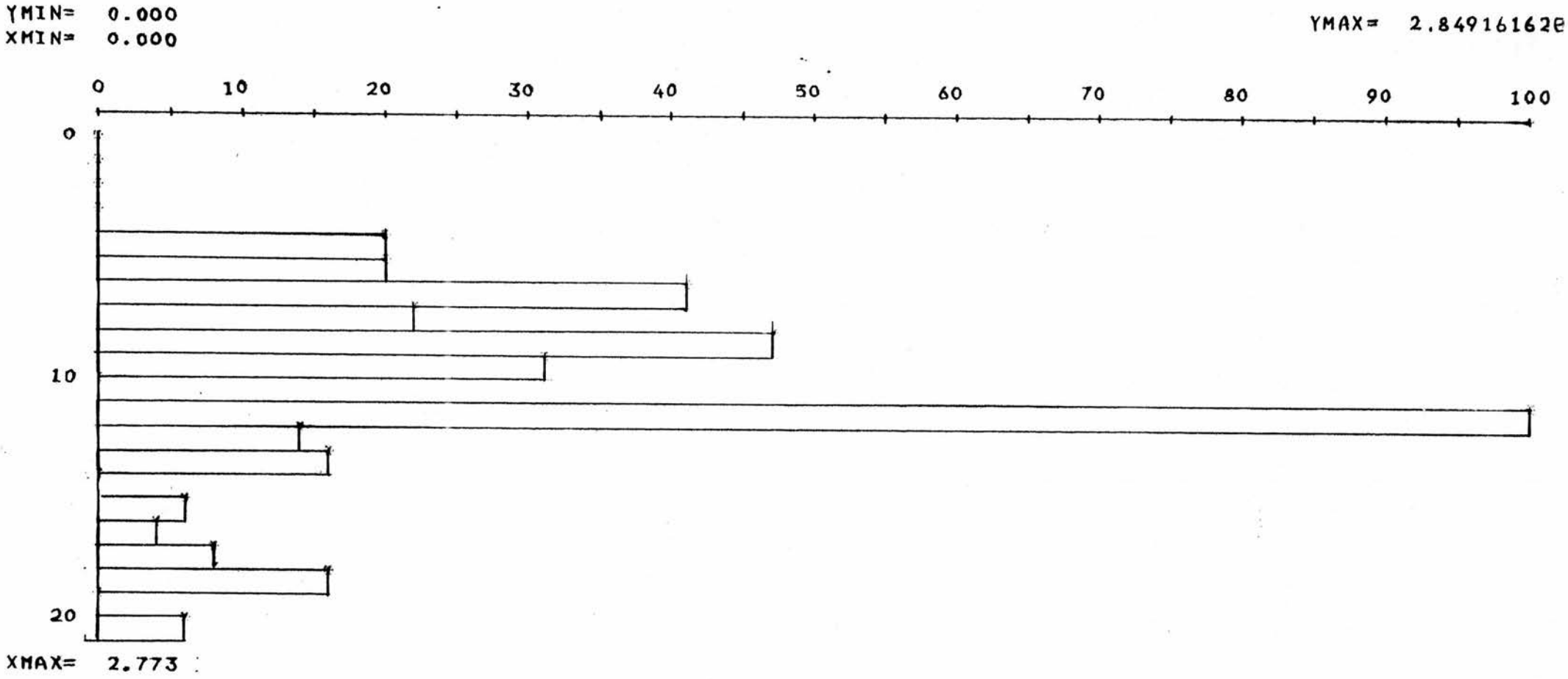


Fig 8.3
Car Available Sample
Level Of Service

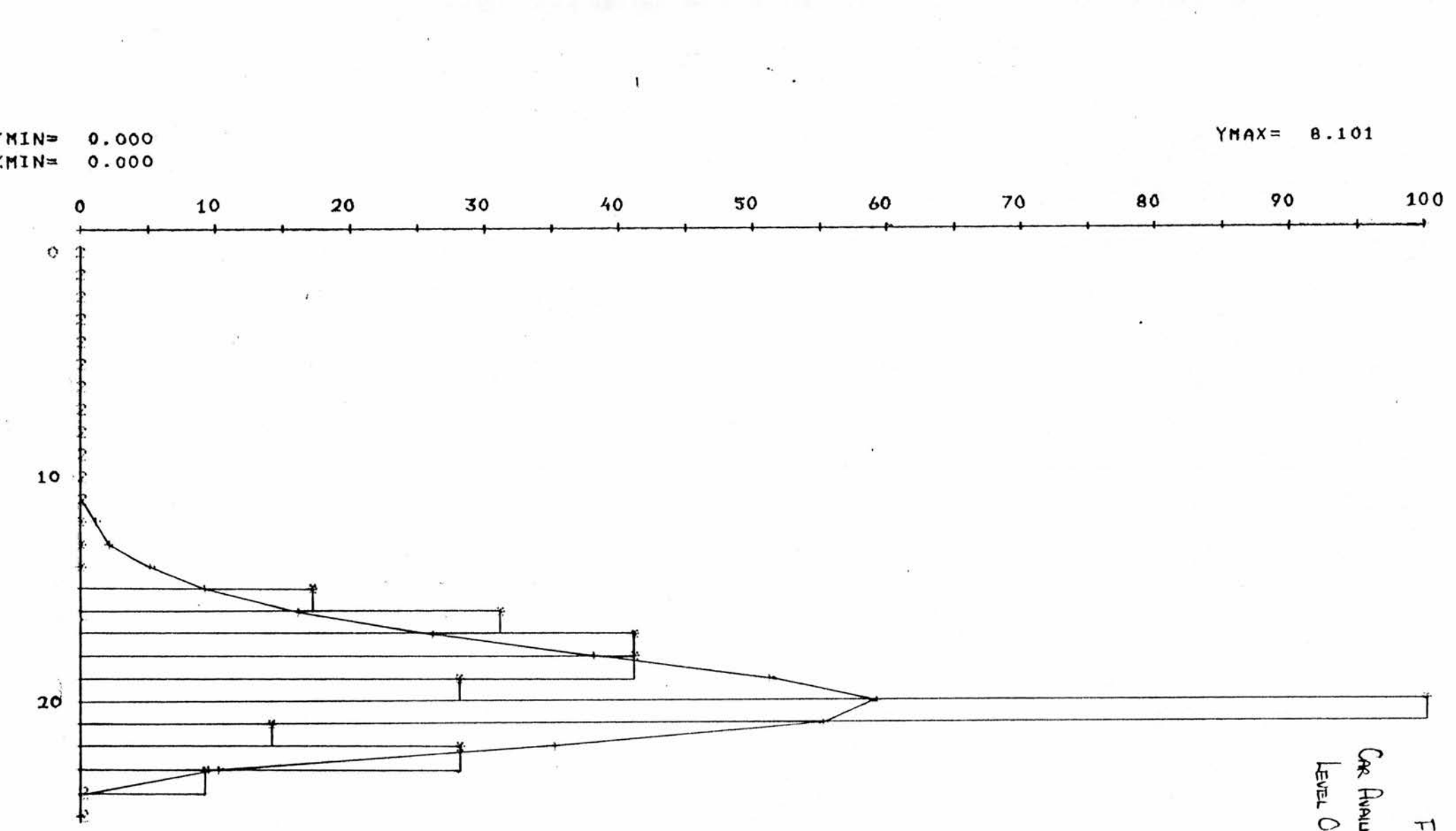


Fig 8.4
Car Available Sample
Level Of Service

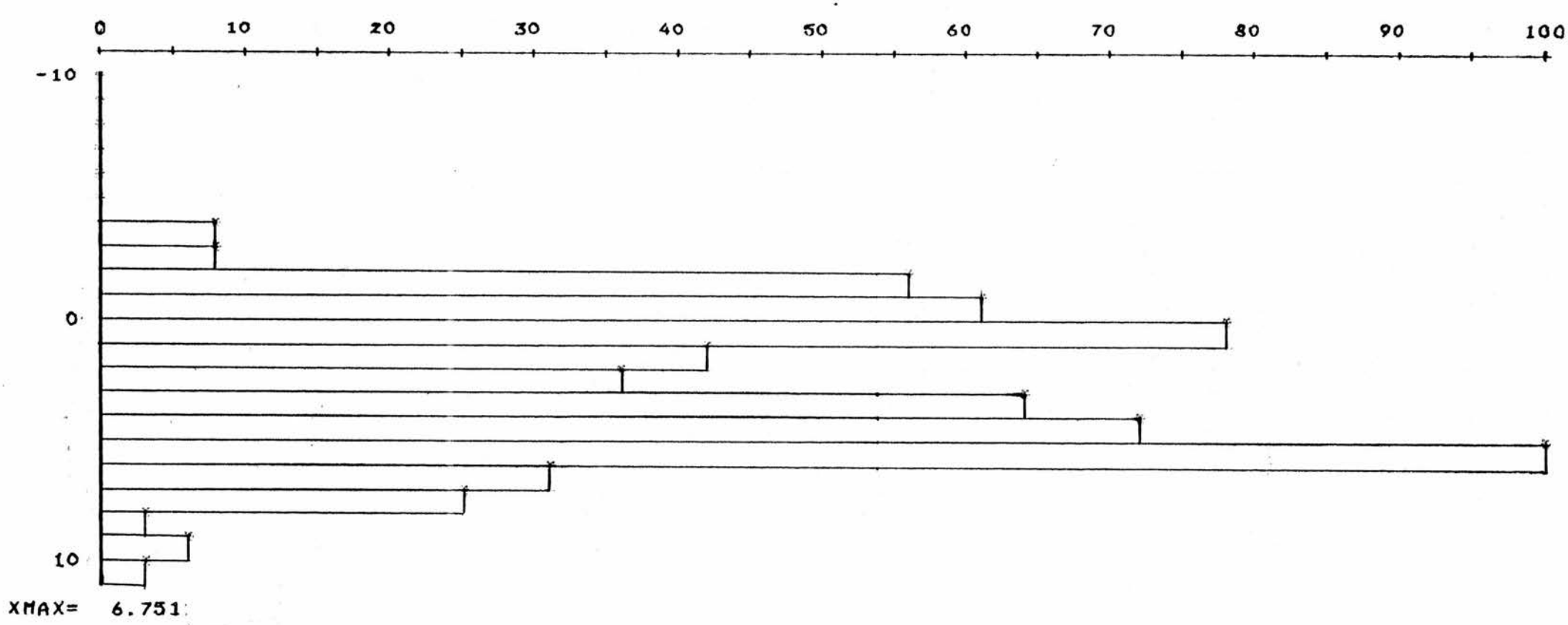


Fig 8.5
Total Sample
Final Model

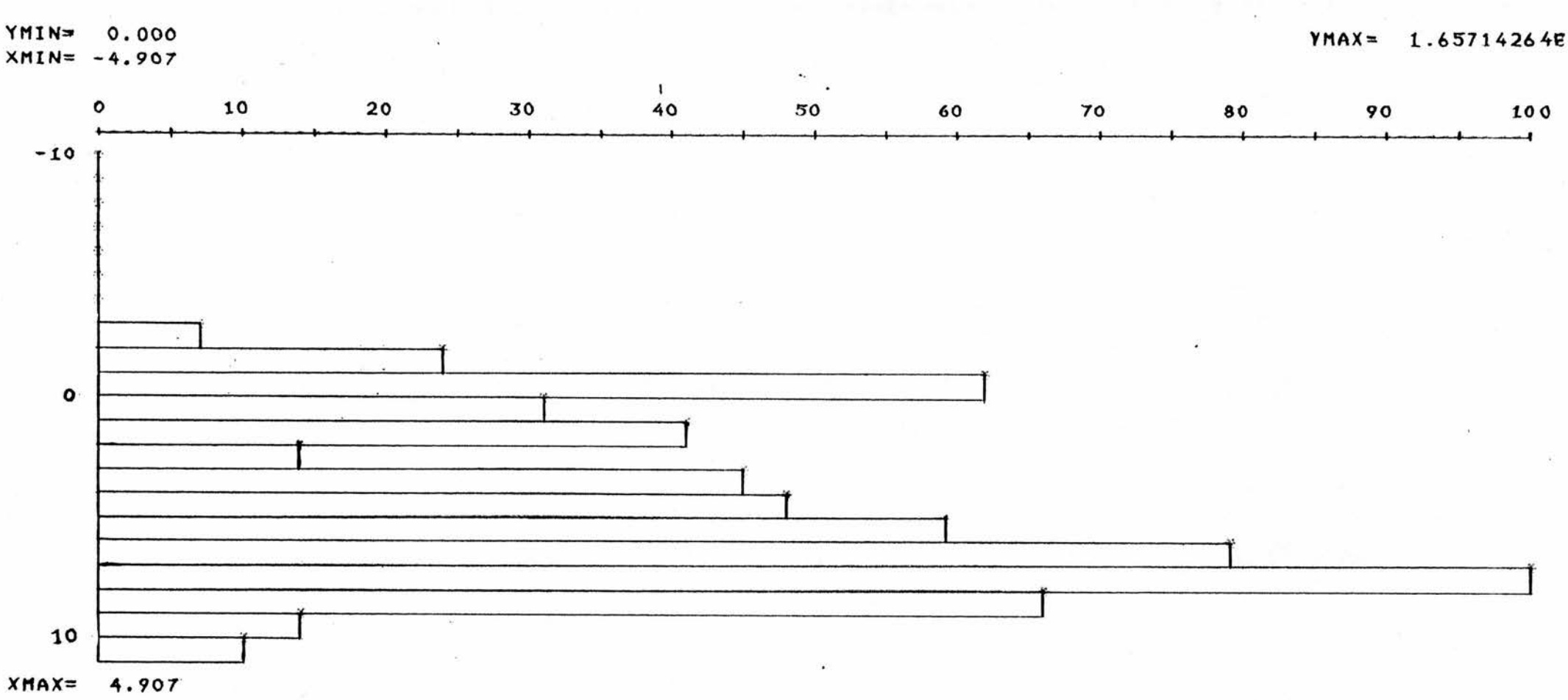


Fig 8.6
Car Available Sample
Final Model

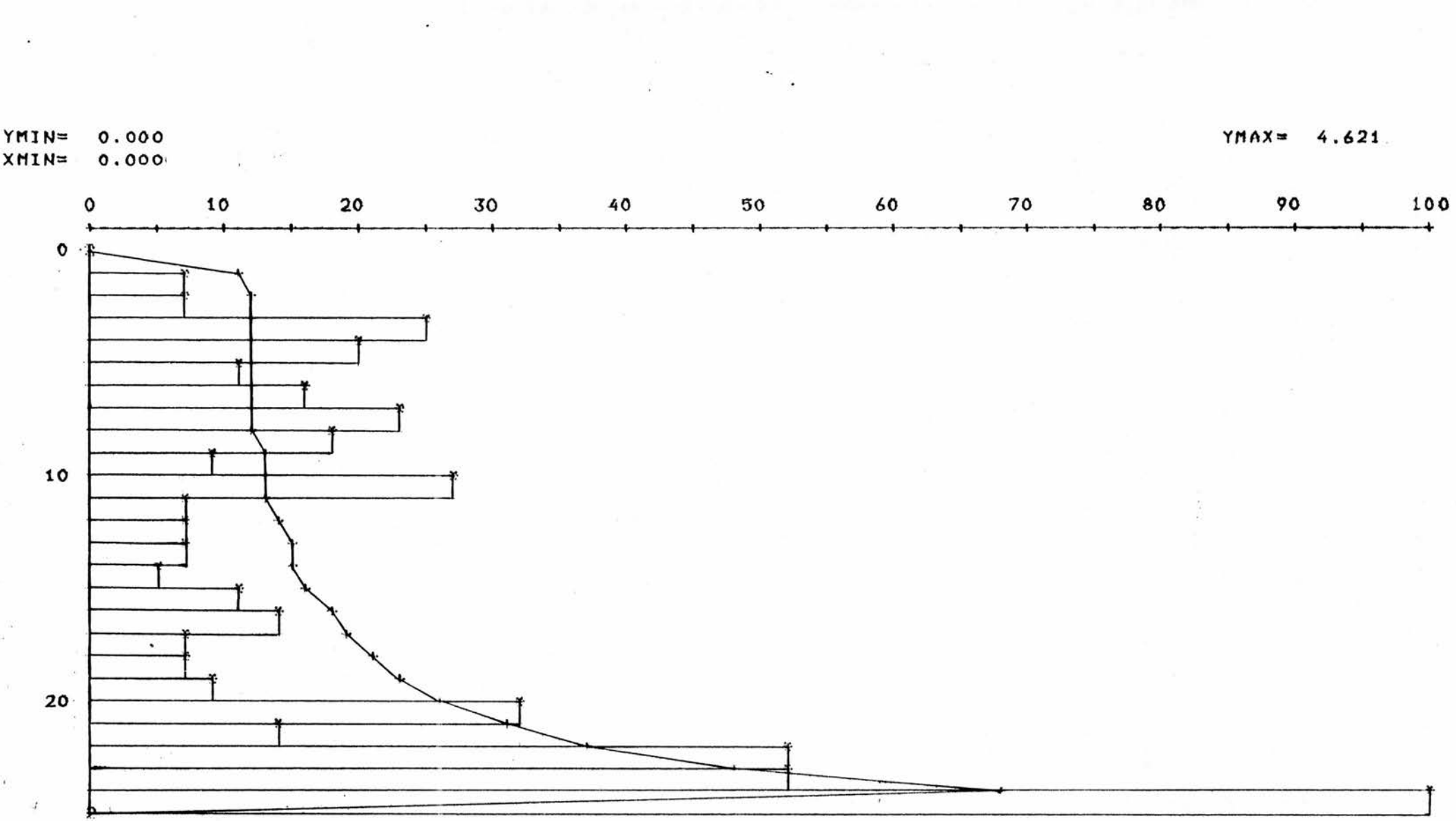
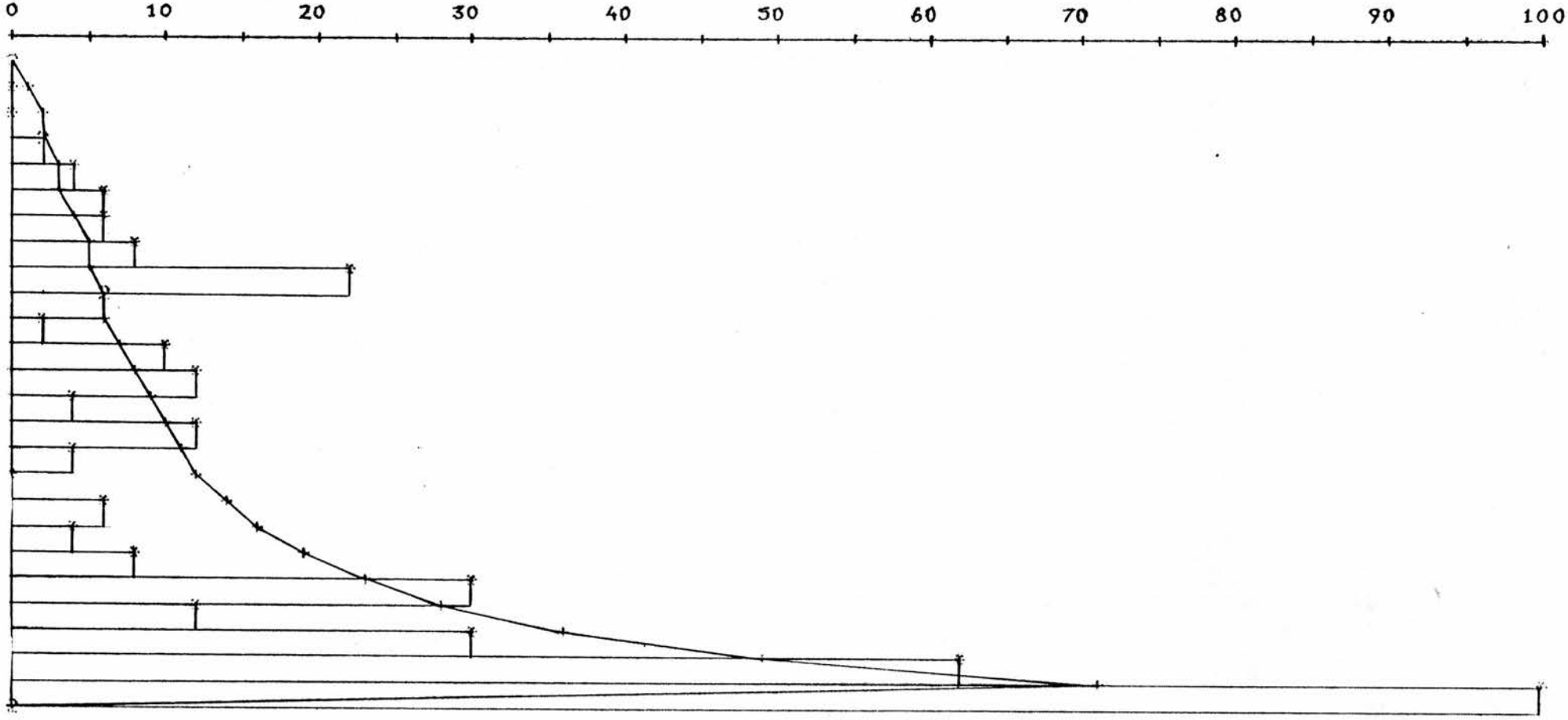


Fig 8.7
Total Sample
Final Node

XMIN= 0.000
YMIN= 0.000

YMAX= 6.367



XMAX= 1.000

Fig 8.8
Car Available
Final Mode

For both samples, the results of the S_B approach would appear to be superior to the other approaches. The shape of the distribution however, introduces an important, practical problem. As Figure 8.6 and Figure 8.7 illustrate, the complexity of the model gives less well behaved distributions than previously with steep peaks at high probabilities. This shape at the extreme values makes the computation of E(P) by numerical integration difficult and imprecise. The S_B distribution is a probability density function and hence should give:

$$\int_0^1 f(p)\,dp = 1$$

In the case of the final model, however, this does not hold and so

$$E(P) = \int_0^1 p\, f(p)\, dp$$

will also be in error. The problem is simply caused by the imprecision of the numerical integration routines at the highly peaked range of the distribution, and although increasing the number of points used to compute the integration increased the precision the result still differed from one.

Previous studies where the S_B distribution has been tested namely Westin (1974), Watson and Westin (1975) [1] used models which were simple level of service variable models and gave fairly well behaved distributions. It is clear that the application of this approach to more complex model forms, with the introduction of socio-economic variables, provides the true test of its usefulness.

1. **Also Talvitie (1973) but he doesn't report the model used.**

In attempting to improve upon the results for the final model it was found that correcting the value of E(P) given by the S_B distribution by

$$E^c(P) = E(P) + \left(\frac{1-T}{T}\right) E(P)$$

$$\text{where } T = \int_0^1 f(P)\,dP \neq 1$$

$E^c(P)$ is corrected E(P)

and hence taking account of the deviation of the total integral from unity gave results which were either very close or identical to the observed proportion, as the results in Table 8.1 show. Although this correction procedure is open to criticism in that the integration error is created only by the peak of the distribution and is thus not uniform across the distribution, empirically it performed remarkably well.

To test the classification approach, the sample was divided into 2 sub-samples and both the average and weighted average computed. The average value for the results was 0.624 with the weighted average 0.735. Although both still differed from the observed proportion they are closer, than the directly estimated naive, thus providing evidence in accord with the belief that classification on the basis of important variables can provide an improvement to the naive, by making the underlying homogeneity assumption more realistic.

Overall, it would appear that it is the more complex model form that provides the true test for the aggregation procedures. The density function performed remarkably well considering the underlying distributions, while the classification approach proved a great improvement over the directly estimated naive. Although the Taylor series expansion approach performed reasonably well, its application to the more complex models did lead to concern over the assumed unimportance of the higher order terms.

As regards previous tests of these approaches, as has been noted, Westin (1974) and Watson and Westin (1975) used the S_β approach on simple model forms with apparent success while Talvitie (1973) using an unspecified model compared the results of S_β , Taylor expansion and naive approaches. Talvities used data from 2 Chicago suburbs both separately, where the S_β and other empirically derived bias corrected naive performed best, and combined, where the naive out-performed the variance corrected (Taylor expansion) procedure, tying with the S_β.

This might be considered to tentatively reinforce the findings here, although it is not possible to deduce futher implications because of the lack of reported information on the model and the $x_i'\beta$ distribution of Talvitie's study.

CHAPTER 9

CHANGES IN CHARACTERISTICS

9.0 INTRODUCTION

The previous chapter was concerned with the methods by which the predictions of aggregate demands (modal share) could be made from the disaggregate models. The next stage is to consider the methods by which predictions can be made of the effect of changes in controllable variables on the level of demand. This is clearly an important aspect of any policy orientated model, allowing the policy maker to evaluate the effects of policy changes, such as a decrease in bus fares on modal shares. Indeed, the analysis can be extended to non-directly controllable variables such as socio-economic variables, if they are in a meaningful form, to evaluate the effect of an anticipated but exogenous change.

Section one considers the importance of the elasticity measures, section two presents the elasticity measures, both point and arc, at the level of the individual; section three presents the incremental logit; section four derives the point and arc elasticity measures at the aggregate level, also considering some approximate measures which simplify estimation; section five then outlines the elasticities based upon the S_B distribution considered in the previous chapter; section six shows how simulation can be made to show the effects of larger changes in the explanatory variables using the S_B distributions; sections seven, eight and nine then present the results of the empirical application of the various measures to the Edinburgh-Livingston study, using the total sample and car available sample estimates. Finally, section ten draws some conclusions from the evaluation of the various measures.

9.1 ELASTICITY MEASURES

When the effects of small changes in the explanatory variables of the model are considered, as in traditional demand studies, it is the

elasticity measure of the responsiveness of demand which receives scrutiny. It is worth noting that in disaggregate models, an elasticity measure evaluating the responsiveness of demand (modal share) to changes in a chosen explanatory variable, is of greater importance than in traditional linear regression analysis.

This results from the fact that the coefficient estimates of the logit model cannot be interpreted as measuring the effect on demand of a one per-cent change in an explanatory variable value. This can be seen as for the logit

$$P_i = \frac{e^{x_i'\beta}}{1 + e^{x_i'\beta}}$$

which implies

$$Q_i = \log\left[\frac{P_i}{1-P_i}\right] = x_i'\beta$$

Hence, the coefficient estimate represents the effect of a unit change in an explanatory variable on Q_i and not directly on the individual choice probability.

That the coefficient estimates do not have a direct interpretation as regards the effect on the choice probabilities implies than an elasticity measure relating the responsiveness of the choice probability to the change would be extremely useful.

9.2 MICRO ELASTICITIES

As disaggregate models are concerned with the individual travellers, it is reasonable to consider the responsiveness of the individual choice probability P_i to a change in a specified explanatory variable (x_ℓ) as an elasticity measure. This can be represented as

$$e_{\ell i} = \frac{\delta P_i}{P_i} \Big/ \frac{\delta x_{\ell i}}{x_{\ell i}} = \frac{\delta P_i}{\delta x_{\ell i}} \cdot \frac{x_{\ell i}}{P_i} \qquad (9.1)$$

This gives [DeDonnea (1971]

$$e_{\ell i} = (1 - P_i)\, \beta_\ell\, x_{\ell i} \qquad (9.2)$$

This measure represents a point elasticity and will only be relevant in assessing small changes about the observed value of $x_{\ell i}$, indicating a trend only at a particular point. To evaluate larger changes would require use of an arc elasticity which can be represented as

$$ae_{\ell i} = \frac{\Delta P_i}{\Delta x_{\ell i}} \cdot \frac{\tilde{x}_{\ell i}}{\tilde{P}_j} \qquad (9.3)$$

$\tilde{x}_{\ell i}$ = value bet. init. and final

$\tilde{P}_i$ = value bet. init. and final

To determine the value of $\tilde{x}_{\ell i}$ and $\tilde{P}_i$ requires determining some point on the response function between the initial and the final value of the variables. The simplest way to do this is to assume linearity, as is often done in conventional demand studies. This would then allow these values to be represented as

$$\tilde{x}_{\ell i} = \frac{x_{\ell i}^A + x_{\ell i}^B}{2} = x_{\ell i}^B + \frac{1}{2}\Delta x_{\ell i} \qquad (9.4)$$

and

$$\tilde{P}_i = \frac{P_i^A + P_i^B}{2} = P_i^B + \frac{1}{2}\Delta P_i$$

A = after change
B = before change

Such an assumption is not unreasonable in the context of the logit as the response function can be well approximated by a straight line within a specific range of $x_i\beta$ as shown on page 58.

This would imply that

$$ae_i = \frac{\Delta P_i}{\Delta x_{ki}} \cdot \frac{2x_{ki} + \Delta x_{ki}}{2P_i + \Delta P_i} \qquad (9.5)$$

Which is a more complex form than the point elasticity as it would require the re-estimation of the individual probabilities for the new value of $x_i\beta$ to evaluate ΔP_i .

9.3 INCREMENTAL LOGIT

A useful property of the logit model is that having estimated the model it is not necessary to re-estimate the complete model in order to compute the change in probability resulting from a change in one of the explanatory variables. This can be achieved by means of an incremental form of the logit model. Consider the effect of a change in the explanatory variable x_k for all individuals i then:

$$\begin{aligned} \overline{x_i'\beta} &= \beta_0 + \beta_1 x_{1i} + \ldots + \beta_k (x_{ki} + \Delta x_{ki}) + \ldots + \beta_M x_{Mi} \\ &= \beta_0 + \beta_1 x_{1i} + \ldots + \beta_k x_{ki} + \ldots + \beta_M x_{Mi} + \beta_k \Delta x_{ki} \\ &= x_i'\beta + \beta_k \Delta x_{ki} \end{aligned} \qquad (9.6)$$

where $\overline{x_i\beta}$ is the resulting value of $x_i\beta$.

Hence the probabilities resulting from the change in x_{ki} can be estimated as:

$$P_i' = \frac{e^{x_i'\beta + \beta_k \Delta x_{ki}}}{1 + e^{x_i'\beta + \beta_k \Delta x_{ki}}} \qquad (9.7)$$

which gives:

$$P_i' = \frac{e^{\beta_k \Delta x_{ki}}}{C_i + e^{\beta_k \Delta x_{ki}}}$$

$$C_i = \left[\frac{1 - P_i}{P_i}\right]$$

Thus the resulting probability can be derived using only the already estimated probability and the change in the relevant explanatory variable, multiplied by it's coefficient estimate. This is clearly a much easier exercise than the re-estimation of the model on the new explanatory variable values.

9.4 AGGREGATE ELASTICITIES

One possible approach to deriving elasticities relating to aggregate behaviour is simply to substitute aggregate values into the micro elasticities. For the point elasticities, this would imply that:

$$E_\ell = (1-\bar{P})\,\beta_\ell\,\bar{x}_\ell \tag{9.9}$$

In this case, $\bar{x}_\ell$ would be the mean value of explanatory variable namely

$$\bar{x}_\ell = \frac{1}{N}\sum_i x_{\ell i} \tag{9.10}$$

and $\bar{P}$ would be either the estimated average probability

$$\bar{P} = \frac{1}{N}\sum P_i \tag{9.11}$$

or the observed proportion choosing the relevant mode, which in the case of the binary logit model with a constant term, gives the same result as (9.11) ie.

$$\bar{P} = \frac{1}{N}\sum y_i \tag{9.12}$$

This would appear to be the approach used by Richards and Ben Akiva (1975) who evaluated the point elasticities based upon the observed average probability and the average value of the relevant explanatory variable. In addition they observed these measures to be linear in β_ℓ and thus represented them diagramatically as straight lines for a given value of $\bar{x}_\ell$ i.e. plotting E_ℓ with $\bar{P}$ for each value of $\bar{x}_\ell$.

Richards and Ben Akiva (1975) further consider that for large changes in the independent variable the mode choice probabilities need to be recalculated thus implying a form for the arc elasticity of

$$AE_{\ell} = (1 - \bar{P}') \beta_{\ell} \bar{x}_{\ell} \tag{9.13}$$

where $\bar{P}_{\ell}'$ is the recalculated average probability resultant on a change in explanatory variable $\bar{x}_{\ell}$.

It would appear on this basis that their measure is somewhat strange simply because of the re-estimation of the average probability. Rather, it is necessary to reconsider the previous micro arc elasticity equation (9.3) and equation (9.5) and reinterpret it in a similar way to the point elasticity giving

$$AE_{\ell} = \frac{\Delta \bar{P}}{\Delta \bar{x}_{\ell}} \cdot \frac{2\bar{x}_{\ell} + \Delta \bar{x}_{\ell}}{2\bar{P} + \Delta \bar{P}} \tag{9.14}$$

Which though requiring the re-estimation of the average probability to compute $\Delta \bar{P}$ is certainly rather different to (9.13).

A major deficiency with this approach to aggregate elasticities is their correspondence to "representative individual" elasticities (in the Marshallian sense), simply using the average values of the variables within the derived micro elasticity form. This means that the distribution of elasticities across the sample is ignored and the results will be biased if the sample is not composed of homogeneous individuals. As Domencich and McFadden note, in most applications there will be a large group of individuals whose choice is clear cut and a smaller group who are sensitive to small changes in the level of service variables which would tend to lead to an overestimate of the response if the above unweighted approach is used.

A more satisfactory approach to the derivation of aggregate point elasticities is to consider the analogue of traditional market demand elasticities, namely the responsiveness of aggregate demand, in this

case market share to a change in the selected explanatory variables average ($\bar{x}$):

$$E_\ell = \frac{\delta \bar{P}}{\delta \bar{x}_\ell} \cdot \frac{\bar{x}_\ell}{\bar{P}} \qquad (9.15)$$

where $\bar{P}$ is the market share (average probability) which could be the composition of a number of market segments weighted by the number of individuals in the segments.

Domencich and McFadden (1975) have shown this to imply an aggregate point elasticity of the form

$$E_\ell = \frac{\sum P_i (1 - P_i) \beta_K x_{i\ell}}{\sum P_i} \qquad (9.16)$$

if a uniform percentage change in $x_{\ell i}$ is assumed for each individual i. This can be written as the weighted average of the micro elasticity

$$E_\ell = \sum \omega_i e_{\ell i}$$

where $e_{\ell i}$ is the individual (micro) elasticity of equation (9.12) and the weight w_i is

$$\omega_i = \frac{P_i}{\sum_i P_i}$$

Thus this measure is a weighted average of the individual elasticities where the weights are the individual's proportion of the total probability.

This is clearly more acceptable than the representative individual approach, taking account of non-homogeneity and, in the situation of a large number of low elasticities and a smaller number with high elasticities, the former group would have a small effect because of their low elasticities, the latter because of their small number. Thus, the aggregate elasticity based on (9.18) will generally be smaller than the result achieved on the basis of the representative individual approach [Domencich and McFadden (1975)].

In deriving (9.16), it was assumed that the change in the relevant explanatory variable was in the same proportion for each individual which may not always be an adequate assumption. Alternatively, if it is assumed that the change is the same for all individuals it can be shown that the aggregate point elasticity is of the form:

$$E_\ell = \frac{\sum P_i (1-P_i) \beta_\ell \bar{x}_\ell}{\sum P_i} \qquad (9.17)$$

Richards and Ben Akiva (1975) note that equation (9.16) will hold for equal absolute changes in the chosen explanatory variable, if the value for the variable is the same for all individuals. For the situation where this does not hold they consider:

$$E_\ell = \frac{\sum_i P_i e_{\ell i} (\bar{x}_\ell / x_{i\ell})}{\sum P_i} \qquad (9.18)$$

where $e_{i\ell}$ is the individual elasticity. This form however, will be problematic computationally if $x_{i\ell}$ takes the value of zero. Anyway, substituting the e_i gives:

$$E_\ell = \frac{\sum P_i (1-P_i) \beta_\ell x_{i\ell} (\bar{x}_\ell / x_{i\ell})}{\sum P_i} \qquad (9.19)$$

$$= \frac{\sum P_i (1-P_i) \beta_\ell \bar{x}_\ell}{\sum P_i}$$

which is the same as equation (9.17).

Analogously to the micro elasticity case, it is necessary to consider an arc elasticity for large changes in the explanatory variables. This can be defined as:

$$AE_\ell = \frac{\Delta \bar{P}}{\Delta \bar{x}_\ell} \cdot \frac{\tilde{\bar{x}}_\ell}{\tilde{\bar{P}}} \qquad (9.20)$$

where $\bar{P}$ represents the average probability, $\bar{x}_\ell$, the average value of explanatory variable ℓ, $\tilde{\bar{x}}$ some point between the initial and post change value and $\tilde{\bar{P}}$ it's average probability analogue. As in (9.4), it is possible and justifiable to simplify by assuming linearity giving:

$$\tilde{\bar{x}}_\ell = \frac{\bar{x}_\ell^A + \bar{x}_\ell^B}{2}$$

$$\tilde{\bar{P}} = \frac{\bar{P}^A + \bar{P}^B}{2}$$

A = value after change

B = value before change

This allows the arc elasticity to be written as in equation (9.14):

$$AE_\ell = \frac{\Delta \bar{P}}{\Delta \bar{x}_\ell} \cdot \frac{2\bar{x}_\ell + \Delta \bar{x}_\ell}{2\bar{P} + \Delta \bar{P}} \qquad (9.21)$$

Again this would require re-estimation of the model to evaluate $\Delta \bar{P}$ which would be done by means of the incremental logit.

There are a number of possible forms for the arc elasticity:

$\frac{\Delta \bar{P}}{\Delta \bar{x}} \cdot \frac{\bar{x}}{\bar{P}}$ using the original $\bar{x}$ and $\bar{P}$ values

$\frac{\Delta \bar{P}}{\Delta \bar{x}} \cdot \frac{\bar{x}}{\bar{P}}$ using the final values of $\bar{x}$ and $\bar{P}$

$\frac{\Delta \bar{P}}{\Delta \bar{x}} \cdot \frac{\bar{x} + (\Delta x / 2)}{\bar{P}^*}$

which was the average value of $\bar{x}$ and $\bar{P}^*$, the actual value of $\bar{P}$ at that value of $\bar{x}$. This last form is the most acceptable, though more difficult to estimate as it requires the actual value of $\bar{P}$ for the given value of $\bar{x}$. It does, however, provide a test on the precision of the linear approximation as used in the first arc elasticity form.

It is possible to develop an approximate form of the arc elasticity of equation (9.21) [Tag el Din (1980)][1] based upon it's relation to the aggregate point elasticity. From equation (9.19), the elasticity for equal absolute changes we can write:

$$\frac{\delta \bar{P}}{\delta \bar{x}_\ell} \cdot \frac{\bar{x}_\ell}{\bar{P}} = \frac{\sum P_i (1-P_i) \beta_\ell \bar{x}_\ell}{\sum P_i}$$

which implies

$$\frac{\delta \bar{P}}{\delta \bar{x}_\ell} = \frac{1}{N} \sum P_i (1-P_i) \beta_\ell$$

Now noting (9.22)

$$\frac{\Delta \bar{P}}{\Delta \bar{x}} \approx \frac{\delta \bar{P}}{\delta \bar{x}}$$

allows the derivation of an approximate arc elasticity from (9.20)

$$AE_\ell = \frac{1/N \sum P_i (1-P_i) \beta_\ell (2\bar{x}_\ell + \Delta \bar{x}_\ell)}{2\bar{P} + 1/N \sum P_i (1-P_i) \beta_\ell \Delta \bar{x}_\ell} \qquad (9.23)$$

which has the advantage of being estimable without re-estimation of the model. Clearly whether or not this is adequate is an empirical question dependent upon the acceptability of (9.22).

Analogously, if the point elasticity measure is considered for equal proportional changes from equation (9.16):

$$\frac{\delta \bar{P}}{\delta \bar{x}_\ell} = \frac{\beta_\ell \sum P_i (1-P_i) x_{i\ell}}{\sum x_{i\ell}} \approx \frac{\Delta \bar{P}}{\Delta \bar{x}_\ell}$$

1 **Though he doesn't derive expression (9.20) nor note the distinction between the absolute and % change elasticity.**

which by analogous reasoning gives:

$$AE_\ell = \frac{\beta_\ell \sum P_i(1-P_i)x_{i\ell}(2\bar{x}_\ell + \Delta\bar{x}_\ell)}{2\bar{P}\sum x_{i\ell} + \beta_\ell \sum P_i(1-P_i)x_{i\ell}\Delta\bar{x}_\ell} \qquad (9.24)$$

where $\Delta x_\ell = INC* \bar{x}_\ell$.

It is interesting to note that although the value of $\bar{P}$ has been interpreted as the average probability, estimated in the model, it is possible to consider analogous elasticity measures based upon the evaluation of E(P) by other means such as the naive, statistical differentials or density function approach. In this manner approximate elasticity measures could be derived for prediction situations for instance, where the estimated model has been applied to other data than the original sample.

9.5 CONTINUOUS ANALOGUES

In the case of the density function approach based upon the S distribution the aggregate point elasticity for a change in the mean value $\bar{x}$ is generally:

$$E_\ell = \frac{\delta E(P)}{\delta \mu} \cdot \frac{\delta \mu}{\delta \bar{x}_\ell} \cdot \frac{\bar{x}_\ell}{E(P)} \qquad (9.25)$$

where $E(P) = \int_0^1 pf(p)dp$ and $\mu = \beta'\bar{x}$

Thus the predicted change in probability resulting from the change in $\bar{x}$ is weighted by the relative frequency distribution to take account of the dependence of this change in the individuals original probability. Westin (1974) has shown that in the context of the logit with the S_B distribution:

$$S_B(\mu, \sigma) \qquad \begin{cases} \sigma = \hat{\beta}'\Sigma\hat{\beta} \\ \mu = \hat{\beta}'\bar{x} \end{cases}$$

that the aggregate elasticity is

$$E_\ell = \frac{E\left(P(1-P)\right)\beta_\ell \bar{x}_\ell}{E(P)} \tag{9.26}$$

It is interesting to note that this measure is the continuous analogue of (9.19) which was derived on the assumption of equal absolute changes in the explanatory variable for all individuals though allowing the original values to differ for all individuals.

As Westin points out, to ignore the RFD would be to extrapolate from the representative individual elasticity, which is the continous analogue of (9.13) namely:

$$E_\ell = \left(1 - E(P)\right)\beta_\ell \bar{x}_\ell$$

This would tend to overestimate the response by the ratio:

$$\frac{E(P)\left(1 - E(P)\right)}{E\left(P(1-P)\right)} \tag{9.27}$$

as we have observed in the discrete case.

In considering the density function approaches the estimted S_B distribution of the probability has both the mean and variance of the linear combination of explanatory variables $x'\beta$ as it's parameters. Hence, it is useful to consider an elasticity measure with respect to the variance as often the change in $x_{i\ell}\ \forall_i$ will affect this parameter. Such a measure is defined as:

$$E_{\sigma^2} = \frac{\delta E(P)}{\delta \sigma^2} \cdot \frac{\sigma^2}{E(P)}$$

where

$\sigma^2 = \beta' \Sigma \beta$

which Westin derives as:

$$E_{\sigma^2} = \frac{E\left[P(1-P)\{\log (P/1-P) - \mu \} \right]}{E(P)} \qquad (9.28)$$

the discrete analogue is

$$E\sigma^2 = \frac{1}{E(P)} \sum_{i} \left[P_i(1-P_i) \{ \log (P_i/1-P_i) - \mu \} \right] \qquad (9.29)$$

The usefulness of the elasticity measures based upon the S_B distribution will clearly be dependent upon the acceptability of the estimated distribution in representing the true distribution of probabilities. Thus a comparison of these results with those of their discrete analogues should provide a test of the acceptability of the restriction imposed by assuming a distribution of the S_B family. The question of evaluating the S_B results when used for forecasting will be considered later.

9.6 SIMULATION

The elasticity measures developed for the S_B distribution have related only to point elasticities applicable only for small changes in the relevant explanatory variables. For larger changes, this approach has the advantage of allowing direct comparison of the S_B distribution incorporating the explanatory variable change, with the initial S_B distribution. Thus, predictions of the effects of changes in the explanatory variable (or a combination of explanatory variables) can be made, merely by evaluating their effect upon the parameters of the distribution.

Considering a change in $x_{i\ell}$ for all individuals which affects only the mean value of the variable; the original S_B distribution is

$$S_B \left(\hat{\beta} \bar{x} \, , \, \hat{\beta}' \Sigma \hat{\beta} \right)$$

and the resulting

$$S_B \left(\hat{\beta} \bar{x} + \hat{\beta}_\ell \Delta \bar{x}_\ell \, , \, \hat{\beta}' \Sigma \hat{\beta} \right) \qquad (9.30)$$

with analogous reasoning from (9.6).

Thus, the value of E(P) can be calculated for the transformed distribution, compared with the original value, and the effect of on E(P) evaluated. It might also be possible to draw conclusions of this effect from visual inspection of the differences between the initial and resulting distributions.

As Westin points out, an additive change in $\bar{x}_\ell$ of $x_{i\ell} + a$ would give a transformed S_B

$$S_B (\beta_k \bar{x}_k + \beta_\ell a , \beta' \Sigma \beta) \qquad (9.31)$$

while a multiplicative change $(1+a)x_{i\ell}$ would lead to the transformed S_B:

$$S_B (\beta_k \bar{x}_k + a \beta_\ell \bar{x}_\ell , \sigma^2 + \beta_\ell^2 (2a - a^2) \sigma^2 + 2 \sum_{k \neq \ell} \beta_k \beta_\ell a \sigma_{k\ell})$$

where $\sigma^2 = \beta' \Sigma \beta$

This implies that in many cases, it will be necessary to consider changes in the variance parameter, requiring the re-estimation of the variance covariance matrix of the variables (Σ) or computation of the new variance as in (9.32).

9.7 EMPIRICAL APPLICATION: POINT ELASTICITIES

The estimates for the various aggregate point elasticities based upon the final model for the total and car available samples are given in Table 9.1. Although some of the reported elasticity values have no interpretive value, such as those for the constant and the dummy socioeconomic variables, they do serve illustrative and comparative purposes.

The results illustrate clearly the differences between the elasticity values and the coefficient estimates, which result from the form of the

ELASTICITY ESTIMATES

TABLE 9.1

	DISCRETE AGGREGATE ELASTICITIES					CONTINUOUS ANALOGUES	
	COEFF	PERCENT	ABSOLUTE	REPRES INDIV	AVERAGE	ABSOLUTE	REPRES INDIV
TOTAL SAMPLE							
LEVEL OF SERVICE MODEL							
CONSTANT	1.001		0.331	0.343		0.330	0.342
TIME	-0.019		0.088	0.091		0.088	0.091
COST	-0.070		-0.194	-0.201		-0.193	-0.201
FINAL MODEL							
CONSTANT	-1.525	-0.296	-0.296	-0.520	-0.520	-0.342	-0.607
TIME	-0.030	0.077	0.082	0.145	0.127	0.095	0.169
COST	-0.072	-0.126	0.118	-0.207	-0.237	-0.136	0.241
NCR2	3.562	0.321	0.443	0.779	0.384	0.512	0.909
DSOC1	1.533	0.027	0.035	0.061	0.029	0.040	0.071
DST	1.169	0.122	0.148	0.261	0.164	0.171	0.304
DSF	-0.869	-0.070	-0.065	-0.115	-0.146	-0.076	-0.134
CAR AVAILABLE SAMPLE							
LEVEL OF SERVICE MODEL							
CONSTANT	1.289		0.285	0.295		0.282	0.295
TIME	-0.036		0.111	0.115		0.110	0.115
COST	-0.062		-0.113	-0.117		-0.112	-0.117
FINAL MODEL							
CONSTANT	0.120	0.018	0.018	0.027	0.027	0.021	0.035
TIME	-0.011	0.020	0.022	0.034	0.028	0.026	0.043
COST	-0.085	-0.119	-0.105	-0.161	-0.187	-0.122	-0.205
NCR2	1.482	0.145	0.174	0.266	0.195	0.202	0.338
DSOC1	1.437	0.022	0.028	0.043	0.025	0.033	0.055
DST	2.081	0.117	0.204	0.313	0.107	0.238	0.393
DSF	-1.099	-0.091	-0.068	-0.103	-0.163	-0.079	-0.132

model, and show the danger of putting too much interpretive value on the coefficient estimates regarding their quantitative effect on the choice probability. The high level of overestimation of the representative individual elasticity, as expected, is apparent - it's values sometimes being double that of the corresponding weighted elasticity. Further, the aggregate elasticities for both absolute and percentage change appear to be of similar magnitude, especially for the continuous (non-dummy) variables. This last feature was to be expected given the small changes involved with point elasticities. Another interesting point is that in this study, the average elasticity is seen to be closer to the weighted aggregate elasticity value than the representative individual measure. The increased homogeneity of the car available sample, however, led to more similar results for the various measures than in the total sample, especially for the representative individual elasticity.

The continuous analogues of the aggregate elasticities based upon the fitted S_B distribution are also shown in Table 9.7. The results portray the same features of overestimation by the representative elasticity as in the discrete forms and although they differ in magnitude from their discrete analogues, this is explained by the error of integration caused by the fitted distribution shape. Indeed, if the crude error correction used for E(P) is used, the results more closely approximate their discrete analogues. However, the more complex form of the elasticity makes such a correction rather more unsatisfactory than when used in the computation of the expected value.

That the S_B elasticities would be similar to their discrete analogues where there are no problems of integration is illustrated in the results shown in Table 9.1 for the simple level of service variable models.

9.8 EMPIRICAL APPLICATION: ARC ELASTICITIES

The various arc elasticity measures developed for percentage changes in the explanatory variables are shown in Table 9.2 and Table 9.3. The arc elasticities of the form which require estimation are:

ARC ELASTICITY ESTIMATES

TABLE 9.2

	CHANGE	AVERAGE PROBAB	REPRES INDIV	POINT ELAST	APPROX ARC	ARC ELASTICITIES 1	2	3	4
TOTAL SAMPLE									
TIME	-10%	0.664	0.143	0.077	0.081	0.080	0.076	0.080	0.080
	-5%	0.661	0.144		0.079	0.079	0.077	0.078	0.079
	5%	0.656	0.146		0.075	0.075	0.077	0.075	0.075
	10%	0.654	0.147		0.073	0.074	0.077	0.074	0.074
COST	-10%	0.667	-0.202	-0.126	-0.119	-0.122	-0.129	-0.121	-0.122
	-5%	0.663	-0.204		-0.122	-0.125	-0.129	-0.125	-0.125
	5%	0.655	-0.209		-0.129	-0.132	-0.129	-0.133	-0.132
	10%	0.650	-0.212		-0.133	-0.136	-0.129	-0.137	-0.136
NCR2	-10%	0.636	0.831	0.321	0.332	0.331	0.343	0.337	0.331
	-5%	0.648	0.804		0.326	0.326	0.332	0.329	0.326
	5%	0.669	0.756		0.316	0.316	0.311	0.314	0.316
	10%	0.679	0.734		0.310	0.312	0.302	0.307	0.312
CAR AVAILABLE SAMPLE									
TIME	-10%	0.773	0.034	0.020	0.021	0.021	0.020	0.021	0.021
	-5%	0.772	0.034		0.020	0.020	0.020	0.020	0.020
	5%	0.771	0.034		0.019	0.019	0.020	0.019	0.019
	10%	0.770	0.034		0.019	0.019	0.020	0.019	0.019
COST	-10%	0.781	-0.154	-0.119	-0.113	-0.113	-0.119	-0.112	-0.113
	-5%	0.776	-0.157		-0.116	-0.117	-0.120	-0.116	-0.117
	5%	0.767	-0.164		-0.123	-0.124	-0.121	-0.125	-0.124
	10%	0.762	-0.167		-0.126	-0.128	-0.122	-0.129	-0.128
NCR2	-10%	0.760	0.279	0.145	0.138	0.143	0.149	0.144	0.143
	-5%	0.766	0.272		0.142	0.144	0.147	0.144	0.144
	5%	0.777	0.259		0.148	0.146	0.143	0.145	0.146
	10%	0.782	0.253		0.151	0.147	0.141	0.146	0.147

ARC ELASTICITY ESTIMATES TABLE 9.2

	CHANGE	AVERAGE PROBAB	REPRES INDIV	ARC ELASTICITIES 1	2	3	4
TOTAL SAMPLE							
TIME	-40%	0.679	0.136	0.089	0.075	0.087	0.089
	-20%	0.669	0.140	0.083	0.076	0.082	0.083
	20%	0.649	0.149	0.071	0.078	0.071	0.070
	40%	0.638	0.153	0.064	0.079	0.065	0.064
COST	-40%	0.693	-0.186	-0.100	-0.128	-0.098	-0.100
	-20%	0.676	-0.196	-0.114	-0.129	-0.113	-0.114
	20%	0.642	-0.217	-0.144	-0.129	-0.145	-0.144
	40%	0.625	-0.227	-0.159	-0.129	-0.163	-0.159
NCR2	-40%	0.548	1.033	0.369	0.422	0.407	0.365
	-20%	0.610	0.890	0.343	0.367	0.357	0.342
	20%	0.696	0.694	0.304	0.284	0.296	0.308
	40%	0.726	0.626	0.291	0.254	0.277	0.298
CAR AVAILABLE SAMPLE							
TIME	-40%	0.777	0.033	0.023	0.019	0.023	0.023
	-20%	0.774	0.034	0.022	0.020	0.021	0.022
	20%	0.768	0.034	0.018	0.020	0.018	0.018
	40%	0.765	0.035	0.016	0.020	0.016	0.016
COST	-40%	0.807	-0.136	-0.090	-0.115	-0.088	-0.090
	-20%	0.790	-0.148	-0.105	-0.118	-0.104	-0.105
	20%	0.752	-0.174	-0.137	-0.123	-0.138	-0.137
	40%	0.733	-0.188	-0.154	-0.125	-0.158	-0.154
NCR2	-40%	0.721	0.324	0.134	0.163	0.139	0.134
	-20%	0.748	0.293	0.140	0.153	0.142	0.140
	20%	0.792	0.241	0.148	0.136	0.146	0.148
	40%	0.811	0.219	0.151	0.129	0.147	0.151

(1) $$AE_{\ell} = \frac{\Delta\bar{P}}{\Delta\bar{x}_{\ell}} \cdot \frac{2\bar{x}_{\ell} + \Delta\bar{x}_{\ell}}{2\bar{P} + \Delta\bar{P}}$$

(2) $$AE_{\ell} = \frac{\Delta\bar{P}}{\Delta\bar{x}_{\ell}} \cdot \frac{\bar{x}_{\ell}}{\bar{P}}$$ using the original $\bar{x}$ and $\bar{P}$ values i.e. those before the change in $\bar{x}_{\ell}$

(3) $$AE_{\ell} = \frac{\Delta\bar{P}}{\Delta\bar{x}_{\ell}} \cdot \frac{\bar{x}_{\ell}}{\bar{P}}$$ using the final values of $\bar{x}$ and $\bar{P}$ i.e. those after the change in $\bar{x}$

(4) $$AE_{\ell} = \frac{\Delta\bar{P}}{\Delta\bar{x}_{\ell}} \cdot \frac{\bar{x}_{1} + (\Delta\bar{x}_{\ell}/2)}{\bar{P}^{*}}$$

where $\bar{P}^{*}$ is the estimated value of $\bar{P}$ at the average value of the $\bar{x}$ i.e. $\bar{x}_{1} + \frac{1}{2}\Delta\bar{x}$.

Considering these results generally, the most striking features are the closeness of the approximate and actual arc elasticities and the expected large over-estimation of the representative individual elasticity. The results for the approximate arc elasticity form are both interesting and useful, implying that it is possible to estimate arc elasticities for this form of model without re-estimation of the model and achieve an approximation very close to the result that does involve re-estimation.

It is clear, however, that the approximate elasticities precision will by its nature behave better the smaller the change, in the relevant explanatory variable, that is involved. The level of over-estimation of the representative individual elasticity, as used by Richards and Ben Akiva (1975) illustrates the danger of using such a measure given heterogeneity within the sample.

The results in Tables 9.2 and 9.3 also show that the degree of error involved is using a point elasticity for anything more than a 5% change

in the relevant explanatory variable can indeed be quite high. The precision of the approximate elasticities will, however, be better the smaller the change in the relevant explanatory variable considered as a result of the implicit linear approximations of the logit response function.

The level of overestimations of the representating individual elasticity measure as used by Richards and Ben Akiva (1975) clearly illustrates the danger of using such a measure for analysis given heterogeneity within the sample. In addition, the degree of error involved in using the point elasticity measure for anything more than a 5% change in the relevant explanatory variable can be seen to be rather high. This error of the point elasticity is however, lower than that reported by Richards and Ben Akiva (1975) because they were comparing it with the representative individual form in their study.

Table 9.4 shows the results for the various forms of the arc elasticities based upon an equal absolute change in the relevant explanatory variables. Not surprisingly, they would appear to be consistent with the features presented by their "percentage change" counterparts.

9.9 EMPIRICAL APPLICATION: SIMULATION

The results of the simulation based upon the fitted S_B distribution for the total and car available samples are shown in Table 9.5. The first result column gives the average probability resulting from the change in the relevant explanatory variable as estimated using the incremental logit, the next two give the average probability and the average probability adjusted to allow for the error in aggregation, as estimated using the fitted S_B distribution and changing only the mean value of the $x'_i\beta$. The remaining columns give the analogous results using the S_B distribution with both the mean and the variances of the $x'_i\beta$ re-estimated together with their values.

It would appear that the crude correction used to allow for integration error works remarkably well for the simulations, making the actual

ABSOLUTE ELASTICITY ESTIMATES TABLE 9.4

	CHANGE	AVERAGE PROBAB	REPRES INDIV	POINT ELAST	APPROX ARC	ARC ELAST
TOTAL SAMPLE						
TIME	-10	0.697	0.128	0.082	0.108	0.107
	-5	0.678	0.137		0.096	0.095
	5	0.639	0.153		0.069	0.069
	10	0.620	0.161		0.055	0.055
COST	-10	0.748	-0.153	-0.118	-0.045	-0.043
	-5	0.704	-0.179		-0.080	-0.079
	5	0.612	-0.235		-0.158	-0.160
	10	0.565	-0.264		-0.202	-0.206
CAR AVAILABLE SAMPLE						
TIME	-10	0.784	0.032	0.022	0.030	0.030
	-5	0.778	0.033		0.026	0.026
	5	0.765	0.035		0.018	0.018
	10	0.759	0.036		0.014	0.014
COST	-10	0.859	-0.099	-0.105	-0.039	-0.035
	-5	0.818	-0.128		-0.071	-0.067
	5	0.720	-0.197		-0.141	-0.149
	10	0.664	-0.236		-0.180	-0.199

	CHANGE	INCREM	APPROX SB SIMUL		SB SIMULATION		AVXB	VARXB
		AVP	E(P)	AE(P)	E(P)	AE(P)		
TOTAL SAMPLE *								
TIME	-40%	0.679	0.644	0.679	0.640	0.677	1.353	4.224
	-20%	0.669	0.638	0.669	0.636	0.668	1.269	4.169
	20%	0.649	0.623	0.648	0.624	0.649	1.099	4.078
	40%	0.638	0.615	0.637	0.617	0.638	1.014	4.041
COST	-40%	0.692	0.650	0.687	0.656	0.691	1.426	3.960
	-20%	0.675	0.641	0.673	0.644	0.675	1.305	4.036
	20%	0.642	0.619	0.643	0.616	0.642	1.063	4.214
	40%	0.626	0.607	0.628	0.602	0.625	0.941	4.317
NCR2	-40%	0.548	0.528	0.538	0.548	0.547	0.270	2.306
	-20%	0.610	0.584	0.600	0.608	0.613	0.727	3.112
	20%	0.696	0.663	0.712	0.616	0.686	1.641	5.330
	40%	0.726	0.678	0.759	0.578	0.701	2.097	6.742
CAR AVAILABLE SAMPLE **								
TIME	-40%	0.777	0.748	0.779	0.746	0.777	1.892	2.717
	-20%	0.774	0.746	0.775	0.745	0.775	1.862	2.698
	20%	0.768	0.742	0.768	0.743	0.769	1.803	2.663
	40%	0.765	0.740	0.765	0.742	0.766	1.773	2.646
COST	-40%	0.807	0.758	0.802	0.769	0.807	2.113	2.516
	-20%	0.789	0.753	0.787	0.758	0.790	1.973	2.592
	20%	0.753	0.734	0.755	0.729	0.752	1.692	2.780
	40%	0.733	0.722	0.738	0.712	0.732	1.551	2.892
NCR2	-40%	0.721	0.703	0.714	0.717	0.723	1.367	2.330
	-20%	0.748	0.726	0.744	0.735	0.749	1.600	2.494
	20%	0.792	0.757	0.797	0.744	0.791	2.065	2.889
	40%	0.811	0.762	0.820	0.733	0.806	2.297	3.122

* AVP=0.958 $\int$SB=0.958 SB: E(P)=0.630 AE(P)=0.658 AVXB=1.184 VARXB=4.120

**AVP=0.771 $\int$SB=0.964 SB: E(P)=0.744 AE(P)=0.772 AVXB=1.832 VARXB=2.680

results very close to the average probability given by the incremental logit. This result is consistent with the previous application of the approximation and further justifies its use empirically, despite its drawbacks. Further, the approximate simulation which considers the effects of the percentage change in the mean of the $x'_i\beta$ s performs well when compared to the method which requires re-estimation of both the mean and the variance. This is clearly a useful result as although the re-estimation of σ does improve the simulation result it is computationally more difficult to derive and if the approximation can be justified empirically, it would certainly save effort. One problem is, however, that the behaviour of the approximate simulation is dependent upon the importance of the variance. This is illustrated by the simulations for NCR2 where the change in the variable has a larger effect on the variance of the $x'_i\beta$ s than that achieved by the time and cost variables, and so the approximate simulation method does not work so well.

Testing the approaches using absolute changes in the time and cost variables gave the results shown in Table 9.6 which again show the similarity in performance between the two methods. In this case, however, the result is to be expected as there will be no effect on the variance of the $x'_i\beta$ s.

This analysis of the effects of changes in the explanatory variables through the fitted S_B distribution can be complemented by a visual inspection of the before and after S_B distributions. For example, Figure 9.1 shows the effect of a 40% decrease in the time difference for the total sample. The main effectt on the distributions which is surprisingly small, is at the low probability range and the peak of the distribution. This implies that if cars become 40% quicker relative to the bus, the effects would mainly be of consolidating those with a high probability of choice, while reducing the number of people at the low probability of choosing car.

9.10 IMPLICATIONS OF THE RESULTS

	CHANGE	APPROX SB SIMUL E(P)	AE(P)	AVXB	VARXB	SB SIMULATION E(P)	AE(P)	INCREM AVP
TOTAL SAMPLE *								
TIME	-10	0.654	0.694	1.486	4.120	0.654	0.694	0.697
	-5	0.673	0.677	1.335	4.120	0.643	0.677	0.678
	5	0.616	0.639	1.033	4.120	0.616	0.639	0.639
	10	0.601	0.620	0.881	4.120	0.601	0.620	0.620
COST	-10	0.674	0.740	1.905	4.120	0.674	0.740	0.748
	-5	0.657	0.701	1.544	4.120	0.657	0.701	0.704
	5	0.612	0.612	0.823	4.120	0.595	0.612	0.612
	10	0.564	0.564	0.463	4.120	0.552	0.564	0.565
CAR AVAILABLE SAMPLE								
TIME	-10	0.751	0.784	1.939	2.680	0.751	0.784	0.784
	-5	0.748	0.778	1.886	2.680	0.748	0.778	0.778
	5	0.741	0.766	1.779	2.680	0.741	0.766	0.765
	10	0.737	0.759	1.725	2.680	0.737	0.759	0.759
COST	-10	0.755	0.852	2.683	2.680	0.755	0.852	0.859
	-5	0.762	0.816	2.258	2.680	0.762	0.816	0.818
	-10	0.659	0.664	0.981	2.680	0.654	0.659	0.664

* AVP=0.659 $\int$SB=0.958 SB: E(P)=0.630 AE(P)=0.658 AVXB=1.184 VARXB=4.120

**AVP=0.771 $\int$SB=0.964 SB: E(P)=0.744 AE(P)=0.772 AVXB=1.832 VARXB=2.680

-40% TIME SIMULATION

Fig 9.1

So far, the concern has been the comparative assessment of the various prediction methods. Although this was an important task, it is also worthwhile considering the implications of the actual elasticity estimates. Firstly, it should be remembered that the elasticities presented for the level of service variables are based upon the variable forms, which are differences. Thus, the elasticities do not represent the response of choice probability to a change in a particular modes' attributes but to a change relative attributes, in this case their differences. The aggregate point elasticity estimates for the level of service variables for the final model were (from Table 9.1).

	TOTAL SAMPLE		CAR AVAILABLE SAMPLE	
	percent	**absolute**	**percent**	**absolute**
TIME	0.077	0.082	0.020	0.022
COST	-0.126	-0.118	-0.119	-0.105

These show, for example, that an equal percentage change in travel time difference will lead to a 0.077 percentage change in the average probability of going by car (or modal share), while an equal absolute change of one minute will lead to a 0.082 change in the average probability. It would appear from the results that changes in relative cost are more effective than changes in relative time and that the total sample shows more sensitivity to both relative time and costs than the car available sample. The elasticities for the relative costs do, however, confirm the findings based upon the coefficient estimates, that changes in the relative level of service variables have little effect upon mode choice, in this case average probability.

The results for the arc elasticities estimates for an increase in time and cost differences (i.e. relative increases in car in-vehicle travel times and costs) were

	CHANGE	TOTAL SAMPLE	CAR AVAILABLE SAMPLE
TIME	5%	0.075	0.019
	10%	0.074	0.019
	20%	0.149	0.034

	40%	0.153	0.035
COST	5%	-0.132	-0.124
	10%	-0.136	-0.128
	20%	-0.217	-0.174
	40%	-0.227	-0.188

The estimates are those of Arc Elasticities 1 and 4 in Table 9.2 and 9.3. These results for the arc elasticities again show relative costs to have more effect than time on the average probability, with the cost elasticities again showing less change across the samples. Comparing these with the point elasticities makes the large degree of error associated with using a point elasticity for anything more than a 5% change in the relative level of service variable evident. Further, these arc elasticity estimates confirm that even large changes in the level of service variables have little effect upon mode choice in the aggregate.

Other studies have provided a variety of elasticity values, but in making comparisons problems of compatibility occur. The significance of the parameter estimates, the form of the elasticity used and the form of the model all contribute to make comparison difficult. However, short run travel demand studies have generally found how elasticities for in-vehicle travel time and travel costs. For example, McFadden (1973) found car in-vehicle time elasticities of 0.13 and car cost elasticities of 0.32. These differ from the findings here in being larger (although still low)

In contrast, however, in their Dutch Study, Richards and Ben Akiva (1975) found direct point elasticities for travel time of 0.26 for car, but did not report any cost elasticities having found costs insignificant to the extent of requiring exclusion from their model. Further, they found an arc elasticity of 0.36 for car showing the importance of not using the

point elasticity for large changes in travel time. These results are, however, overestimates as they were computed on the basis of the representative individual elasticity measure, but even when compared with the same measure for this study they provide higher values.

There are, of course, problems in making such comparisons as these studies reported direct elasticities using the actual value of time and cost for the specific alternative, rather than using relative times and costs as in this study. The elasticity results presented here are thus restricted forms of those presented in the studies mentioned. So although they are comparable, the restrictions imposed must be borne in mind.

CHAPTER 10

CONCLUSIONS AND IMPLICATIONS OF THE ANALYSIS

10.0 INTRODUCTION

This final chapter draws together the main conclusions of the study and their implications. This involves tying together the analyses undertaken, clarifying the rationale behind the study by expressing it at a more general level, and considering the general implications of the empirical results obtained. To this end, section 1 deals with the context of the analysis as presented in Chapters 2 and 3; section 2 considers the subject of car ownership and mode choice following on from Chapter 6; section 3 presents the main conclusions and implications of the empirical analyses of Chapters 5,6 and 7; sections 4 and 5 deal with the conclusions and implications of the aggregation and prediction studies considered in Chapters 8 and 9; and lastly, section 6 considers topics for future research.

10.1 NEW TOWNS

Although the development of New Towns in Britain far from represented a homogeneous planning entity, they did differ from orthodox developments to the extent that they represented a unique experiment in urban and regional development which has had international influence. The comprehensive planning of the New Town environment mainly on virgin sites, or a small existing base, provided the possibility of putting into practice many ideas of planners, freeing them from the constraints of an already established urban structure. In this way, the New Towns represent a most interesting subject of study, not only their successes but also their failures, providing information on the possible developments of urban structures in a more general context. Thus, the future of urban development could be the creation of independent structures containing the successful features of New Towns and the lessons learned, or simply the integration of successful features of New Town developments to existing urban structures. Even if there is complete disregard of all aspects of the New Towns, it is the lessons learned from the British experience that will have provided the basis for judgement.

A major aim of this study has been to provide information on the determinants of transport mode choice for the journey to work in New Towns by means of a case study of Livingston. In this way this most important aspect of travel behaviour has come under scrutiny for a New Town which had as one of its fundamental planning concerns the development of an efficient transport system. Being representative as was seen in Chapter 2 of the second wave of development of New Towns, Livingston reflected the impact of increasing car ownership on life styles, a concern for the aim of balanced commuting rather than that of self containment, and the use of New Towns as regional growth centres. The extensive concern for the transportation network in the town, its extreme commuting levels, and its generally high car ownership level was argued in Chapter 3 to have resulted in Livingston's transport system representing half the fundamental transport planning choice facing towns and cities. Describing how they would appear if

emphasis was placed on the use of cars and on walking as a complement to public transport. As a result, the information provided by this study on the determinants of mode choice for the journey to work adds to the understanding of the effect of possible urban transportation planning options at a more general level.

In pursuing this aim it was important to analyse the structure of Livingston so as to provide a context for the analysis. In Chapter 3 Livingston was found to be a most useful subject for analysis as it reflected many of the features of New Town development in an extreme form. The main reason for this was its high population and employment growth from a small predesignation base. This gave Livingston in the seventies, the most youthful population of all New Towns, the highest proportion of males and the highest average household size. The small amount of housing inherited at designation also meant that Livingston had a high standard of housing stock and amenities, with an extremely high proportion of publicly rented properties.

In terms of its industrial and employment structure, Livingston showed an extreme of the New Town characteristic of bias towards manufacturing employment, with an over-representation of skilled manual workers. Related features however, showed the speed of adaption of the town to its regional setting. Its high rates of unemployment in the 70's, despite the high growth of employment, and its deficiency of service employment, reflecting its role within the West Lothian region (unemployment was high relative to the New Town average but not high for the region). Livingston's role and importance in the region was further emphasised by its high in and out commuting levels with Edinburgh taking the major flow of commuters and providing the professional and service employment lacking in the town. Not surprisingly, given its levels of commuting, Livingston had the common New Town feature of high car ownership, with a concentration of one car owning households.

The physical development of Livingston, as mentioned, reflected

concern for personal mobility and increasing car ownership. Its compact linear shape reflected its transport orientated development, with its road system precluding through traffic from residential areas and minimising flow delays within the town. The town's segregated footpath system, unique to British New Towns, complemented its public transport service (with minimised walk times to bus stops) as an alternative to the car. These developments are clearly important, especially in the context of minimised work journeys within the town, as the location of the majority of employment in peripheral industrial estates allowed walking to be a feasible alternative in modal choice.

In this way, the analysis of Chapter 3 justified the choice of Livingston as the object of study for the empirical analysis, both in terms of its novelty value and the implication for potential future transport developments in more conventional urban developments. Thus, a study of the major out commuting journey to Edinburgh, and a study of the journey to work within the town were made. Before moving on to present the main conclusions of the analysis, a necessary prerequisite is a return to the discussion of mode choice and car ownership as developed in the text.

10.2 CAR OWNERSHIP AND MODE CHOICE

In the study, the estimation results were reported for both the total sample and a sample of individuals whose household owned at least one car. This was justified in Chapter 6, by reference to the different implications of the two samples for the treatment of car ownership, namely the possibility of introducing bias by not including individuals whose households did not have a car if car ownership choice is endogenous to mode choice and conversely if it is exogenous. This reasoning was sufficient for the purposes of providing the final model forms. To assess the models and the implications of the results, however, it is necessary both to generalise the analysis of car ownership and to make more precise the practical form and inherent constraints imposed by the data. These tasks are undertaken in this section with reference to the way in which other studies have handled such problems.

Essentially the analysis involves considering the following inter-related issues, which are all affected by the practical form of the study.

1. Endogeneity - This issue was considered in Chapters 4 and 6 and concerns the treatment of the relation of the various transport choices of which mode choice is only one. More specifically, in this context, it concerns the issue of whether or not car ownership choice can be considered endogenous or exogenous to mode choice for the journey to work.

2. Aggregation - Again, this issue was considered in Chapter 6. It relates to the level of which choices are made, either at the household or individual level, and whether or not individual choices can be aggregated to provide household choices. A further aspect is the practical complication of the form of the available data which can often conflict with the level of choice.

3. Non-linearity - This concerns the problems of relating the measurement of constraints to observed actions. It is possible that discontinuities, non-linearities of behaviour, can exist with respect to the value of constraints. The most obvious example is the number of cars owned by a household. It might be expected that household behaviour would show a qualitative change in moving from a zero car to a one car ownership level which would differ from that for 2 or more cars.

4. Non-observed constraints - Primarily this issue relates to the fact that any true decision structure can be unobserved and so a priori judgements at a conceptual level can differ markedly, while empirical verification may not be possible as the real constraints may not be observable. Thus, the individual analysts in working with observed constraints as proxies can differ markedly in their view of the true decision process, while their empirical analyses may not allow comparative assessment. This issue might be considered a catch all as it clearly relates to the first three issues.

As was seen in Chapter 6, the complexity of the analysis of transport choices, even at the level of the independent consideration of the car ownership and mode choice for the journey to work, is immense. This implies that the creation of any practical analysis requires some simplification, both in terms of assumptions required analytically and in terms of those necessitated by the practical constraints of the data. When this is combined with the fourth issue, it would appear that any particular decision structure, even the simplest one of independence of the two choices, can be justified by recourse practical limitations, or at least not be open to empirical refutation by other more complex models. This is not to say that more complex models might not be more realistic, but to argue that it is difficult to assign levels of realism in the circumstances and even if analytical superiority is achieved the practical form of the more complex models might not achieve superiority.

Before moving on to a more precise analysis of the practical form of this study, it is worthwhile considering the approaches adopted in other studies. Generally, transport decisions are considered to be conditional on employment location and residential location choice, which are often considered as long run choices. There is, however, less uniformity in the treatment of the shorter run work and non work transport choices. In analysing car ownership and mode choice for the journey to work most studies for example, Domencich and McFadden (1974) have tended to consider the choice of mode for the journey to work to be a short run decision made conditional on the level of car ownership. Others, for example, Lerman and Ben Akiva (1976), Ben Akiva and Atherton (1977) and Train (1980) have considered the car ownership choice to be endogenous to the mode choice decision and have postulated models of joint car ownership/mode choice for the journey to work. In this way, these choices have been seen as medium range decisions with trip frequency, destination, mode and route choice for non work trips being labelled as short run choices[1] made conditional on the longer run one.

1. **See Ben Akiva and Atherton (1977).**

This joint choice approach, in explicitly taking into account simultaneity, was thus argued to improve upon the pure mode choice studies which paid lip service to simultaneity merely by the inclusion of variables to reflect car ownership constraints.

Although the joint choice models certainly do have plausibility they also have a number of important problems. Analytically, they still require the simplifying assumption of choice hierarchies of a block conditional form (simultaneous choices in the block, independence between) and can be criticised if one considers some other structure relevant. In addition, there is the problem of specifying the actual form of the simultaneity, whether purely simultaneous or recursive and if recursive the direction of choice and the existence of feedbacks have to be considered. Then of course there is the problem of aggregation. Mode choice is usually taken as an individual decision and car ownership a household decision, which together with the treatment of the choices of differing levels of car ownership, composition of the household and decision structures within the household cause problems for the models and tends to lead to rather cavalier assumptions. At a practical level, the issue of non-observed constraints takes effect. For example, it is necessary to specify the co sts of car ownership in modelling car ownership choice. In the studies mentioned this takes the form of an average annual cost of car ownership. This is clearly a necessary simplification, given the lack of reported costs or information on type, age, condition, etc...of the cars, but might not reflect the cost constraints of the households adequately. Even if such information was available, however, reported costs might be considered poor estimates (because of reporting bias) while measured costs would tend to require numerous simplifying assumptions, which might well detract from the usefulness of the resulting estimate.

It would appear that none of the models treat the complexity of the constraints, decision making procedures and family relationships, which govern mode choice, car ownership or car usage adequately. Indeed, even if an adequate model was available the data generally available, and more specifically that available for this study, are inadequate for

the calibration of such a model. It is thus inevitable that trade offs will occur in choosing a simple robust data compatible model and given the data and the practical constraints of the present study, the most effective use of the available sample was the sample separation procedure used in the text.

This sample separation provided samples containing those individuals whose household had at least one car available and those individuals who were heads of households, as well as the total sample. The implications of the car available selection was to provide a sample of individuals who had access to a car at least in terms of their household owning one. The definition of the dependent variable differed from other studies in that, for reasons of lack of information on car sharing (which drivers took passengers) and relative times and costs, etc. (See Chapter 5), car choice was defined as car use, whether driver or not. Thus, every individual was a potential car user, but clearly there would be non-linearity in behaviour between individuals having a car available in the household and those who didn't. For this reason, the car available sample was created. This is a more complex reasoning than the exogeneity/endogeneity reasoning which sufficed for the creation of the final model forms, but its implications are more clear cut. Essentially, the car ownership choice is considered exogenous to the mode choice, with constraints on car usage being reflected in the car availability explanatory variables. Thus, the sample separation can be seen to allow, as well as the total sample, two distinct subgroups, namely those with direct access to a car, and those who are heads of their households within which one would expect great homogeneity of behaviour.

10.3 MAIN CONCLUSIONS OF THE EMPRICAL STUDIES

Studies of the determinants of transport mode choice models were undertaken using disaggregate behavioural probabilistic choice models for two journeys. The first, in Chapters 5 and 6, used a binary logit model and was the choice between car and bus for the journey to work in Edinburgh, by far the most important out commuting trip. The second, in Chapter 7, was the journey to work within Livingston which used a multinomial model for the three available modes of car, bus and walk.

The journey to work within Livingston is of great interest as it reflects the general features of New Town developments, namely the minimised and efficient work journeys and the feasibility of walking as an alternative to car and bus (indeed walk was second in importance to car for this journey). Both the car and bus modes have the advantages of efficient road networks without the usual urban bottlenecks and walk time to bus stops are minimised by design (the majority of dwellings being within 400 metres of a bus stop). These features are relevant only at the origin of the journey to work in Edinburgh. This journey, over a distance of 14 miles on less efficient road systems, also has the destination characteristics of Edinburgh which are more typical of urban travel conditions, such as parking difficulties, the requirement of bus transfer and traffic delays. Although, as was seen in Chapter 5, there are deficiencies in the representation of destination characteristics, for practical reasons, their effects should still be manifest (although maybe not directly) in the empirical results.

Another important aspect of the journeys considered in the study was the types of commuters engaged in the particular journeys. Appendix 7 outlines the differences in socioeconomic characteristics between households containing at least one worker in Edinburgh and the total sample. Those households containing one or more workers who commuted to Edinburgh were concentrated in the higher social claass and socioeconomic groups and reflected the related features of lower unemployment, smaller household size and much higher levels of car ownership, than those for the town as a whole. Also, the individual characteristics of the Edinburgh commuters reflected the importance of Livingston within its regional context and the importance of Edinburgh in providing the service and professional employment which was not available in Livingston. Livingston showing the characteristic New Town bias towards manufacturing employment.

Certainly one of the major conclusions of the analysis concerns the success of the models used when calibrated on data not specifically designed for them, together with measured level of service values. Although it would be advantageous to have "custom made" data for

such studies, the fact that disaggregate behavioural models have been shown to perform well on traditional travel survey data[1], widens their applicability and practical feasibility. Also, given their advantages over traditional models, it adds support to their claim for more general usage.

In Chapter 7, the different specifications of the models used for the two journey types together with certain practical limitations made comparisons of the results difficult and, at the level of the relative coefficient values somewhat tentative. Useful conclusions were achieved by such an exercise, however, and it is worthwhile presenting the major conclusions of the studies in such a manner. Before doing so, the problems involved in making a more general comparative assessment need to be considered.

At a conceptual level, the models employed here have the advantage of a consistent theoretical structure based upon the traditional consumer theory of utility maximisation. In attempting to compare the results obtained from this study with those of other studies it must be remembered, however, that any empirical study even if based upon the same models will be, at a practical level, the product of much ad hoc empirical manipulation (used to overcome practical limitations) and based upon many differing conventions. These considerations will tend to preclude any detailed comparisons of empirical results across different studies. General conclusions, however, can be drawn for example, on the relative weightings of the various determinants of mode choice, whether they bare high or low, in support or in contradiction to generally held views of their relative importance. Comparisons of this nature are clearly of importance.

Although it might be argued that the various studies of transport mode choice (using disaggregate probabilistic models) undertaken represent a

1. **Other studies have achieved the same for example, DeDonnea (1971); McFadden (1974); Domencich and McFadden (1975).**

fairly heterogeneous grouping various subgrouping of similar forms of studies can be discerned. Thus, one might define wide categories of inter and intra urban studies, or possibly subdivide intra urban into trips to the central business district and cross town trips. Problems will, however, remain in making comparisons as studies will differ by for example, the country of the study and related transport conditions, mode availability and distances involved. In the study presented here the above problems are compounded by the unique form of development implied by the UK New Towns, with the specific object of study, namely Livingston, representing many of the New Town features in an extreme form. It is clearly difficult to categorise the journey to work in Edinburgh either as inter or intra urban study and, as was seen, the features of Livingston make the study of commuting within the town somewhat unique. The problem is, however, only one of categorisation and hence of determining in any comparative assessment similarity with other studies. Indeed this presents the exciting prospect of expanding the practical application of the models employed in the study and drawing conclusions as to the effects of the form of New Town development on mode choice behaviour by comparison with studies of more orthodox urban forms. A prospect made more interesting by the claim that such New Town developments can be considering to represent half the fundamental choice facing town and cities. In this way, the importance of this study lies in the provision of results for a New Town. Comparison with other studies are relevant at a general level, in providing a framework within which to judge differences and similarities and conclusions are tentative.

The most striking results of both empirical studies was the apparent lack of importance of the level of service variables as determinants of mode choice. This finding both in terms of coefficient magnitude and significance for in-vehicle travel time and travel cost was consistent across both studies and across the sample separations employed. Both variables were less heavily weighted and less significant for the within Livingston study although for the heads sample, the coefficient of the

time variable did not comply with a priori expectations. These findings imply that the level of service variables, excluding excess time and costs are not significant in determining choice of mode, although they are more important for the longer journey, as would be expected. Unfortunately, the lack of significance of the time and cost variables precluded the estimation of any meaningful value of time estimates from the studies.

Such a conclusion is not inconsistent with the findings of other studies [1]. However, the coefficient magnitudes and significance are rather lower than those generally found. This together with the elasticity estimates would appear to imply that the importance of such level of service variables is lower within the environment of the New Town, than in more orthodox urban forms. Further, in contrast to most other studies, the cost variable was found to be more significant than the in-vehicle time variable.

Unfortunately, given the empirical evidence showing the greater importance of excess travel time relative to in-vehicle travel time, the studies were somewhat deficient in their treatment of walk and wait time. For the Edinburgh-Livingston journey the attempts to create a bus walk time variable was unsuccessful, although it did provide some evidence to support the belief that excess time is more heavily weighted than in-vehicle time. For the within Livingston journey, bus walk time successfully illustrated this differential weighting and achieved significance, except in the car available sample. Its coefficient magnitudes were generally lower than those found in other studies [2]. This, however, probably reflected the success of the planned minimisation of dwelling/bus stop distance in Livingston.

1/2 **See for example: McFadden (1974); Domencich and McFadden (1975); DeDonnea (1971); Richards and Ben Akiva (1975); Quarmby (1967); Lisco (1967). Any comparisons are however, only at a general level given the divergence of the forms of the studies.**

Certain excess time effects of the destination were incorporated into the journey to work in Edinburgh model by the use of the time of travel dummy (peak/not peak), and were found to be of importance. This was not so for the within Livingston journey, a fact which underlines the efficiency of the New Town's transportation road network, its lack of bottlenecks making the time difference between peak and non-peak travel minimal.

Car ownership and mode choice have already been considered at a conceptual level in the previous section. At a practical level the models included a car constraint variable, the number of cars per full time employed member of the household (NCR2) or the number of cars per household member (NCR1). These commonly used variables were intended to reflect the constraint on car usage within the household and, as is generally found,were highly significant. For the journey to work in Edinburgh NCR2 performed best, while for the within Livingston journey, excepting the total sample, NCR1 performed best. This finding was in keeping with intuitive reasoning. For the longer commuting journey, it would be expected that the claims of employed household members on any available car would predominate, while for the shorter journey other household claims would be expected to be more relevant, given the availability of walking as a feasible alternative and the short journeys involved. Thus, for instance, the claims of housewives to use the car to shop or take children to school would be more likely to affect the using the available car for work journeys. Unfortunately, the practical constraints of lack of data on car allocation such as the number of licence holders in the household, precluded pursuing this analysis any further.

As regards the available socioeconomic information a number of variable forms at both the household and the individual level were experimented with. Although there was no information available on the income levels of households or individuals, it was possible to create soc ial status variables, and given the well known inadequacies of most reported income data, the use of such variables was considered to provide adequate proxies for the effects which income would be

considered to measure. At the household level [1], DSOC1 which was a dummy variable based upon the professional/non professional dichotomy performed well for the journey to work in Edinburgh. That this was preferred to the white collar/blue collar dummy DSOC, reflected the nature of the commuters to Edinburgh, who were predominantly in professional and service employment, and reflected the higher car usage of those in professional households. Further, there was also a predominance of professional heads of households which resulted in the failure of the variable for the heads sample. For the journey to work within Livingston, neither of the social status proxies were found to be significant. This is not surprising for DSOC1 but it might be expected that DSOC would be important. The explanation of its failure is most likely the failure of DSOC as a proxy for income and social status effects or that these effects were adequately reflected in the car ownership and individual characteristics variables.

For both studies, DST a dummy varible reflecting the head/not head of household distinction was significant. This, not surprisingly, reflects the importance of the priority of the head of household in car usage. The effect was more significant for the longer journey to Edinburgh for the total sample and of similar significance for the car available sample. Further, DSAE which reflected the male/female head of household distinction, was significant for the heads sample for the within Livingston journey implying that male heads of households are more likely to travel by car.

Overall, these results imply that the choice of mode for the journey to work both within Livingston and to Edinburgh is determined mainly by factors other than the levels of service of the available modes. Such a conclusion has important consequences given the possibility that new urban structures might attempt to include features of the New Town

1. **In actual fact, this information was based upon the head of household. This is, however, the usual practice in defining such household characteristics.**

transport systems. It would appear that the directly controllable policy variables of time and cost have little effect upon the choice of mode of the individual. Thus attempts to increase the efficiency of buses as an alternative to car, or even to lower the cost of public transport, will not have a significant effect on patronage. The success of New Town planning would appear to be in the minimisation of work journeys to allow walking as a feasi ble alternative but this has probably had a greater effect upon bus than car patronage. This general conclusion does raise difficulties for planning transport policies, but in some ways the conclusion that car usage is mainly determined by car availability and the related social class and status of the individual might appear self evident.

10.4 AGGREGATION AND PREDICTION

Although disaggregate models have clear benefits over traditional aggregate models in analysing the determinants of travel choice, a crucial consideration in the practical use of such models is their ability to make the predictions required by policy makers. Such predictions are by necessity concerned with aggregate shares and so it is necessary to provide some form of aggregate model based upon the estimated disaggregate models. As was seen in Chapter 8 such "aggregated" models have the advantage of the underlying disaggregate structure and an explicit aggregation assumption, rather than the implicit aggregation assumption of zonal homogeneity required by purely aggregate models. There are, therefore, advantages to delaying aggregation to the last possible moment but there is then the problem of deciding on the form of aggregation procedure.

Despite the importance of this topic, it has been surprisingly neglected in the literature. As was seen in Chapter 8, few studies have been concerned with comparing the available aggregation methods and many have simply used the least complex approach upon encountering the problem. The choice of aggregation procedure however, is largely an empirical question and hence comparative empirical assessments are a

necessity. For this reason, Chapter 8 was concerned with the practical application of the available procedures, using the journey to work between Edinburgh and Livingston study (as more procedures are available for binary than multinomial logit) and so adding to the sparse evidence on their performance.

The aggregation procedures considered were:

1. **naive** - which simply uses the estimated parameters and the means of the explanatory variables.
2. **statistical differentials** - which considers the distribution of the explanatory variables by reference to the moments of their distribution.
3. **density function** (S_g) - where the distribution of the choice probability estimates are weighted by the probability density function based upon the explanatory variables.
4. **classification** - where the members for the prediction group are assigned to homogeneous classes and a weighted average of the naive estimates for each class used.

Each of these procedures ws compared to the average probability computed by complete enumeration of the sample. Estimates were made for both the total and car available samples, for both a simple model containing only the level of service variables (and a constant) and the final model forms.

For the simple model the results of the various procedures were similar to the observed proportion, the higher value of VARXB (the variance of the linear combination of parameters and explanatory variables) generally leading to less precision for the car available sample. The true test of the procedures came when they were applied to the more complex final model forms. Here the density function approach when adjusted for integration error performed remarkably well considering the complexity of the underlying distributions. The classification approach provided a great improvement over the directly estimated naive but not as great as that provided by Talvitie's (1973) empirical

bias correction. Although the Taylor series expansion was reasonably close (for the car available sample) to the observed proportion it was less satisfactory than the other measures for the total sample. Here, VARXB was less for the car available sample and resulted in superior estimates for all the procedures (especially the statistical differentials approach).

Generally, these results can be considered to support the findings of other such studies. Watson and Westin (1975) successfully used the S_β approach on simple model forms, while Talvitie's (1973) comparative analysis, although not reporting the model used, found the S_β and the corrected naive performed best and found the naive outperformed the statistical differentials approach.

Although the classification procedure improved upon the naive it did not perform as well as might be expected. Its performance can clearly be improved by better classification, but given the problems of attaining adequate sample sizes within the classes, the S_β approach might be considered for use in its place (especially when its usefulness in predicting the effects of changes in explanatory variables is considered), as might the corrected naive (although this has the disadvantages of a somewhat ad hoc derivation).

Overall, the use of disaggregate models to provide aggregate predictions would appear to present flexibility in applications and to overcome the practical limitations presented by the study. They underline the importance of the trade off between bias in simple procedures and the practical problems of more complex approaches. In choosing a particular method it is clearly necessary to bear in mind the limitations of the approaches and to consider how they are to be used.

Having dealt with the aggregation issue in Chapter 8, Chapter 9 investigated the related methods by which predictions can be made of the effects of changes in policy controllable variables. This concerned the use of various forms of elasticity measures and of simulations based upon the estimated S_β distribution.

Elasticity mesures were seen to be of great importance in predicting the effects of changes in theexplanatory variables on the modal share, because the coefficient estimates do not have a direct quantitative interpretation with respect to the choice probabilities. There are, however, a number of methods of evaluating both point and arc elasticity measures at at aggregate level. For the point elasticity, there is the "representative individual" elasticity based upon the micro elasticity form but the average variable and probability values, then there is the analogue of the traditional market demand elasticities (for equal absolute changes or for equal proportionate changes in the relevant explanatory variable). For the arc elasticity there are a number of forms, one based upon the assumption of linearity (using average of the before and after values); one using the original variable and probability values; and one using the average of the before and after variable values and its actual probability value. This last measure is more difficult to estimate than the others but provides a test of the precision of the measure based upon the linear approximation. In addition to these measures, an approximate form of arc elasticity, which does not require re-estimation of the average probability was presented for both equal absolute and equal proportionate explanatory variable changes. Lastly, some continuous analogues of the elasticity measures, based upon the S_B distribution were presented.

These elasticity measures were estimated for the simple level of service and final model forms on both the total and car available sample, for comparative assessment. The representative individual elasticity was seen to provide the expected high level of over-estimation, indeed evaluating the individual (micro) elasticities and simply taking the average gave an estimate closer to the weighted elasticities. In addition, because of the small magnitude of the changes involved in point elasticities, the estimates for equal absolute and equal proportionate changes were found to be of similar magnitude. The discrepancies were, as expected, lower for the estimates based upon the more homogneous car available sample.

The continuous analogues of the aggregate elasticities based upon the fitted S_B distribution showed the same over-estimation by comparison with the representative individual form. The results of these measures, however, differed from the discrete forms for the final model results. This was because of integration error and although the crude error correction improved the results the more complex form of the elasticity measure made this relatively more unsatisfactory than when used in the computation of the average probability. The results for the simple level of service model forms were, however, more successful and remarkably close to the discrete estimates.

For the arc elasticity estimates, the representative individual form again showed its expected over-estimation while the approximate arc elasticity measures were remarkably close to the computationally more demanding forms. The precision of the approximate forms, of course, greater the smaller the change in the relevant explanatory variables considered. The results also illustrated that the use of point elasticities can provide a high degree of error for any explanatory variable changes greater than 5%. These results were consistent for both the equal absolute and equal proportionate elasticity forms. As regards the relative performance of the arc elasticities, the measure based upon a linear approximation of the change in both variable and probability gave the same estimates as the measure which used the estimated probability for the value of the variable, and these provided the yardstick to evaluate the approximate elasticity form. The measures using the original and final values of the variables and probability values performed less adequately, as would be expected.

In addition to the elasticity measures, the effects of changes in characteristics were simulated by adjusting the parameter of the estimated S_B distribution of probabilities. This process was found to be informative in allowing analysis of the changes in distribution, once the practical problem of integribility was overcome. The approximation of entering the variable changes only through the mean parameter of distribution (keeping the variance constant) was found to be close to the more complex approach where the new variance was also computed, though this was related to the size of VARXB.

Overall, the results illustrate the dangers of using representative elasticity forms (as Richards and Ben Akiva [1975] do) when the sample is heterogeneous, and of using point elasticities to predict the effects of large changes in the relevant explanatory variable. In addition, the approximate forms of arc elasticity with its computational advantages, was found to perform well. Further, the empirical results were found to compound those conclusions already expounded in the study, namely the lack of importance of the level of service variables as determinants of mode choice for the journey to work in Edinburgh. Commuters appear to be more responsive to changes in travel costs than in in-vehicle travel time, but both having elasticity estimates much lower than those found in other studies. Further the S_g simulations were consistent in illustrating the lack of responsiveness of choice probability to changes in the level of service variables. Clearly the choice of measures used will involve a trade off between bias in simple procedures (although the approximate measures presented here have performed well) and the practical costs of the more complex measures. Again, it is necessary to bear in mind the limitations of the measures used, in interpreting them and to consider their adequacy in the use for which they are required.

10.5 TOPICS FOR FUTURE RESEARCH

Any study of this nature will be constrained by the practical limitations of available data, and the imposition of personal constraints on the scope of the analysis to make it practically feasible. These considerations, together with the surprisingly expansive development of research on disaggregate behavioural travel demand models, mean that the analyses presented here could be expanded in numerous directions. However, limiting the suggestions to the level of a possible agenda for only one large and dedicated research team there are a number of obvious extensions which would be of great interest:

1. Although the study illustrated that disaggregate behavioural models can be successfully calibrated on existing data designed for orthodox travel studies, it would clearly be of advantage to

obtain specially tailored data. This would allow a number of practical limitations mentioned in the text to be overcome and would expand the activities that could be modelled.

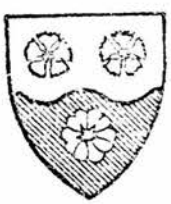
2. Related to the first suggestion, it would be interesting to be able to empirically model car ownership and mode choice together and attempt to discover the relation between these two choices.

3. It would be of interest to undertake the aggregation and prediction analyses of Chapters 8 and 9 for the multinomial study of the journey to work within Livingston.

4. It would clearly be of use, having studied Livingston, to apply to same models to other New Towns to provide comparative assessments. This would also allow testing of the transferability of models from one New Town to another.

APPENDICES

APPENDIX 1



gston Development Corporation

Chairman:
B. D. Misselbrook, C.B.E., B.A., F.B.I.M.
General Manager:
S. E. M. Wright, B.Eng., C.Eng., F.I.Mech.E.

Livingston, West Lothian, EH54 7AD
Telephone: Livingston 31177 TELEX: 727178

Your Ref:

17th January, 1975

Householder,

re again askir, residents in Livingston for help with planning the town.
time we are asking one in five of all households, selected on a random
s, for details of travel. Information about where people travel to
, to shop and for recreation, and how many people have the use of cars
help with the planning of roads and with the provision of public transpo .

lso need further help with proposals for a railway station for the town.
is why there re questions asking if you would use a railway station.
hould be made clear that this refers to the southern railway line through
town, with a station near Bellsquarry.

ough some of the questions ask only about travel to Edinburgh, this is
because the survey is being carried out in conjunction with the Lothian
onal Council. All trains would also go to Glasgow.

ough the questionnaire looks long it can be completed in about 10 minutes.
of the questions only need a tick in the appropriate box. A member of
Corporation staff will call on you in the next few days to collect the
ey. He will be able to help with any sections you have been unable to
in and to answer any questions you may have. All your answers will of
se be completely confidential and there is no need to put your name or
ess on the form.

I thank you very much for your help.

s sincerely,

ewman Brown,
f Architect and Planning Officer

tion development corporation

ployment and travel to work

Travel Survey

give the following information for ALL MEMBERS OF THE HOUSEHOLD

give relation- Head of ld (e.g. son) f Household	Age if under 21	Full or Part-time Worker, Unemployed, Retired, Student, Schoolchild, Housewife

ch EMPLOYED PERSON in the Household please add the following information

ame and Address of Employer	What is your occupation: please describe fully	How do you get to work. PLEASE READ NOTES 1 & 2	When do you start and finish work. If shifts please state variations.	What is your door to door journey time	
				TO work	FROM work

you go to work by car, please state if you are the driver or a passenger.

you are a member of a CAR POOL (each person taking his car in turn) please ate 'car pool'. Please add the number in the pool in brackets, e.g. car pool (2 your partner(s) in the pool are in the survey please arrange for only ONE rson to fill in the number.

w many CARS/VANS (licensed as private) does your household own? ☐

members of your household have regular use of OTHER CARS .g. Firm's) please indicate number. ☐

w many MOTOR CYCLES/SCOOTERS/MOPEDS does your household own? ☐

one in the household regularly makes trips after work BEFORE returning please give details.

rom? ct)	where to?	for what purpose?	how often?	by what means?	final arrival time at home.

E WHO WORK IN EDINBURGH HAVE TO ANSWER QUESTIONS 5 to 13

		YES	NO
u need a car at work in Edinburgh?	1st person listed in Qu.2 as working in Edinburgh		
	2nd person		

		YES	NO
u answered 'YES' in question 5, are upplied with a car by your employer?	1st person		
	2nd person		

AVEL TO WORK IN EDINBURGH BY CAR

		YES	NO
u have a private parking place nently available at work?	1st person		
	2nd person		

t, where do you park your car?	1st person	
	2nd person	

uch does it cost you daily to	1st person	pence
	2nd person	pence

ong does it take you to get your parking place to work?	1st person	mins.
	2nd person	mins.

		YES	NO
u use a bus for this part of work trip?	1st person		
	2nd person		

do you estimate the daily cost ur car journey to Edinburgh? se exclude any parking charge in qu. 9)	1st person	pence
	2nd person	pence

AVEL TO WORK IN EDINBURGH BY BUS OR TRAIN

u have changed from car to bus or train for the journey to work in urgh since 1973 was this because of :

		YES	NO
rking restrictions in ntral Edinburgh	1st person		
	2nd person		

		YES	NO
e increase in the cost of trol and motoring generally	1st person		
	2nd person		

		(a)	(b)
a combination of (a) and (b) ich was the more important?	1st person		
	2nd person		

ublic transport

ith the proposal for a RAILWAY STATION in Livingston, we need to know how many ld be likely to use a Station if one were built JUST SOUTH OF BELLSQUARRY. swering Qu. 14, please read the notes following the question.

O ANY MEMBER(S) OF YOUR HOUSEHOLD USE THE TRAIN FOR TRAVEL TO :

EDINBURGH YES ☐ NO ☐ If YES, how many? ☐

GLASGOW YES ☐ NO ☐ If YES, how many? ☐

ou decide whether you would use a railway station, please assume that the approximate times and costs will apply in relation to TRAIN TRAVEL.

TIMES to EDINBURGH 25 mins. to GLASGOW 60 mins.

FREQUENCIES

EDINBURGH Dep. Livingston 7.10, 8.00, 8.20 a.m. and at 2 hr. intervals through the day, with extra train at 6.55 p.m. Dep. Edinburgh every 2 hrs. with 5.25, 5.40, 6.35 p.m. in evening peak.

GLASGOW Dep. Livingston 6.30, 7.30, 8.00, 8.20, 9.30 a.m. and at 2 hr. intervals through day except evening peak. Dep. Glasgow every 2 hrs. with 4.50, 5.50 in evening peak.

FARES to EDINBURGH 63p Day Return and £2.80 Weekly Season
to GLASGOW £1.12 Day Return £5.00 Weekly Season

TING for example 25 mins. and 17p (single) from Deans, 20 mins. and 17p.
RVICES from Knightsridge, 15 mins. and 12p from Craigshill.

ient FREE CAR PARKING FACILITIES at the station.

rative purposes the following approx. information is given on BUS JOURNEYS rgh and Glasgow.

TIMES e.g. from Deans to Edinburgh 65 mins:to Glasgow 95 mins.
Knightsridge to Edinburgh 51 mins:to Glasgow 100 mins(48 mins expre
Craigshill to Edinburgh 44 mins:to Glasgow 111 mins(60 mins expre

FREQUENCIES

rom Edinburgh: Service 27/35 via Midcalder – ½ hourly throughout the day
Service 200 via Broxburn – ½ hourly at peak periods,hourly off-peak
Service 201 via Midcalder – hourly throughout the day.

rom Glasgow: Service 14 express – Dep.Livingston 6.30 a.m.,Dep. Glasgow 5.30 p.m
Service 200/201 to Bathgate,then 16 – ½ hourly throughout the day
Service 27/35 – ½ hourly throughout the day.

: 15 TO 18 ONLY HAVE TO BE ANSWERED BY THOSE WHO SAID IN QUESTION 14 THAT
LD USE THE TRAIN FOR TRAVEL TO EDINBURGH

n using the train what would be the MAIN REASON for the journey?

	To/From Work	Education	Shopping	Social and Recreational	Business Firm's/Personal
on					
on					
on					
on					

would you TRAVEL TO the station?

	on foot/ bicycle	by bus	by driving a car and parking READ NOTE BELOW	by person driving you then going elsewhere	as car passenger other than previous col.
on					
on					
on					
on					

f it may be in a car pool (each person taking his car in turn) please tate 'car pool'.

the reason you would be using the train to get to Edinburgh is NOT WORK

	how often would you be going?	on what likely day(s)?	at what time(s) of day?
on			
on			
on			
on			

what DISTRICT(S) or STREET(S) in Edinburgh would you be going?

	District or Street in Edinburgh
on	
on	
on	

...er journeys

...lp us in planning the town if we know where people have to travel at the ... shopping and recreation.

... you please give details of WHERE your household goes for SHOPPING

	Place(s) visited	Usual method(s) of travel
... once a week		
... once a week		

... you please give details of WHERE members of your household go for ...EATION and ENTERTAINMENT.

	Place(s) visited	Usual method(s) of travel
... once a week		
... once a week		

...OULD BE VERY PLEASED TO RECEIVE ANY OTHER COMMENTS YOU WOULD LIKE TO MAKE ...T TRAVEL FACILITIES IN LIVINGSTON.

THANK YOU VERY MUCH FOR YOUR HELP!

APPENDIX 2

EXPECTED SIGNS OF COEFFICIENTS

An important consideration in the empirical evaluation of the variable forms is the success of the signs of the coefficient estimates to accord with a priori reasoning. These expected signs can be derived from the relation between the variables and their effects on the probability of choice. Considering the binary logit:

$$Q_i = \log (P_i/(1 - P_i)) = x'\beta$$

The log of the odds of choosing the car mode is determined by the linear combination of the variables and their coefficients. Thus, if the probability of choosing the car (P_i) were to decrease then $P_i/(1-P_i)$ would also decrease, and hence so would Q_i.

For the difference form of the variables consider X_k = CT-BT. Now an increase in X_k can either as a result of a change in CT or BT. For a change in CT which increases X_k

$$CT + \Delta CT - BT > CT - BT$$
$$\Delta CT - BT < - BT$$
$$\Delta CT > 0$$

and for a change in BT which increases X_k.

$$CT - (BT + \Delta BT) > CT - BT$$
$$- (BT + \Delta BT) < - BT$$
$$\Delta BT < 0$$

Thus, an increase in X_k will be caused by either a decrease in travel time by bus or an increase in travel time by car. It is to be expected that either of these would make the car mode less desirable relative to the bus. Thus P_i would be expected to decrease and so Q_i would decrease meaning that a negative sign is expected for the coefficient of X_k. By analogous reasoning the same negtive relation between a change in X_k and the resulting change in probability will hold for an increase in X_k and, of course, the analysis can be

generalised to allow for changes in both CT and BT as only the final effect on X_k will be relevant.

If the same reasoning is employed for the ratio, relative difference and log of ratio variable forms the same conclusions regarding the expected coefficient signs is found.

APPENDIX 3

REPORTED vs MEASURED DATA

It is interesting to consider the relation between those times reported by the individual travellers, and those engineered for the study. Such an analysis has the problem of the coding used in the survey data and the non-availability of data on the non-chosen mode. These can be overcome, however, by imposing the same coding on the engineered data and considering only the chosen mode. Thus Table A1 shows a cross-tabulation of the bus time reported by individuals who travelled by bus and the corresponding engineered value, while Table A2 shows the same for those who travelled by car.

There is, in making such an analysis, the further problem that the reported travel time relates to door to door travel time while the engineered relates to in vehicle travel time. However, little can be done about this because of the non-availability of destination excess time estimates, however, in Table A1, the estimated in vehicle travel time plus origin excess time are given in brackets (for the non-null cells).

It would appear that for the bus travellers, the estimated and reported values relate fairly closely, as expected the lack of excess time estimates cause the measured values generally to underestimate the reported values. This feature being further underlined by the improvement afforded by adding excess origin time to the measured in vehicle travel times. This relation is not so clear for car travellers although the nature of the coding clearly makes analysis difficult.

REPORTED VS MEASURED DATA TABLE A1

REPORTED \ MEASURED	⩽10	11-20	21-40	41-60	61-90	91+	TOTAL
⩽10	0	0	0	0	0	0	0
11-20	0	0	0	0	0	0	0
21-40	0	0	10 (4)	7 (13)	0	0	17
41-60	0	0	12 (4)	25 (31)	1 (3)	0	38
61-90	0	0	2	16	1 (5)	0	19
91+	0	0	0	1	0 (1)	0	1
TOTAL	0	0	24	49	2	0	75

CAR TRAVELLERS A2

REPORTED \ MEASURED	⩽10	11-20	21-40	41-60	61-90	91+	TOTAL
⩽10	0	0	0	0	0	0	0
11-20	0	0	14	0	0	0	14
21-40	0	6	75	0	0	0	81
41-60	0	0	45	1	0	0	46
61-90	0	0	3	0	0	0	3
91+	0	0	0	0	0	0	0
TOTAL	0	6	134	1	0	0	141

APPENDIX 4

GOODNESS OF FIT MEASURES

In measuring the goodness of fit of a model, the analyst is attempting to show the accuracy of the estimated model in approximating observed data. When using the logit model however, the conventional goodness of fit statistics, as used in linear regression analysis, are not applicable because of the non-linearity of the relationship and the limited nature of the dependent variable. It is possible to use "t" tests on the individual coefficients, however, as the maximum likelihood estimates are assymptotically normally distributed and assymptotically unbiased.

To test the models as a whole involves testing the hypothesis that the dependent variable is independent of the values of the explanatory variables. As the null hypothesis this can imply either that each alternative has the same choice probability as if all coefficients constrained to zero, or influenced by alternative specific effects only, where all coefficients except for those for the alternative specific constants are constrained to zero. This test of the null hypothesis can be made by the likelihood ratio that which considers the random variable $-2 \log\lambda$.

$$\text{where } \lambda = \frac{L(\hat{\beta}o)}{L(\hat{\beta}o,\ldots\hat{\beta}_k)}$$

and $L(\beta o)$[1] is the value of the likelihood function evaluation at the null hypothesis, and $L(\hat{\beta}o,\ldots\hat{\beta}_k)$ the value of the likelihood function for the estimated model. For large samples, $-2 \log\lambda$ is distributed χ^2 with K-1 d.o.f.

1. For binary choice model

$$L^*(\hat{\beta}_o) = C \log C/N + (N-C)\log\left(\frac{N-C}{N}\right)$$

where N = number observations; C = number choosing car DeDonnea (1971).

degrees of freedom where K is the number of independent variables including the constant (for the binary logit). Thus, the larger the value of -2 $\log \lambda$, the higher will be the confidence with which the null hypothesis can be rejected.

More generally -2 $\log \lambda$ will be distributed with K degrees of freedom where K is the difference in degrees of freedom between two models. This allows the likelihood ratio test to be used to test whether a model improves significantly over the fit of another nested within it rather than simply to test the null hypothesis, which can often be trivial.

Although, as noted, the coefficient of determination R^2 is inappropriate for the logit, a number of statistics have been developed as analogies, usually denoted as ρ^2 McFadden (1973) and Ben-Akiva (1973) consider:

$$\rho_1^2 = 1 - \frac{L^*(\hat{\beta}_0, \ldots, \hat{\beta}_K)}{L^*(\beta_0)}$$

$$0 \leq \rho^2 \leq 1$$

where L* represents the log of the likelihood

Now although ρ^2 will lie between zero and one, the nature of the logit model means that a perfect fit would give a value of about 0.7 McFadden (1973), indeed Hensher (1980) considers a value between 0.2 and 0.4 to imply a good fit. This measure can be adjusted for degrees of freedom to give

$$\rho_2^2 = 1 - \frac{L^*(\hat{\beta}_0, \ldots, \hat{\beta}_K)/K}{L^*(\hat{\beta}_0)/N-K+1}$$

A further "pseudo R^2" put forward by Burns et al (1976) developed by Cragg ( ) is

$$\rho_3^2 = 1 - \exp\left\{-2\left[L(\hat{\beta}_0, \ldots, \hat{\beta}_K) - L(\hat{\beta}_0)\right] / N\right\}$$

While McFadden (1973) associates ρ_1^2 to a inferential procedure by showing

$$\left[\frac{K+1}{K}\right]\left[\frac{\rho_1^2}{1-\rho_1^2}\right] \sim F_{K,K+1}$$

which he terms the log likelihood index.

The χ^2 test for the log likelihood ratio has been criticised, Stopher (1975) for being rather a weak test, as it generally produces values of χ^2 much larger than those found in conventional tables, making it difficult to compare alternative formulations on this basis. As we have seen, however, although the test of the model against the null hypothesis may often be trivial, this approach can clearly be used to compare nested models. A further criticism of the log likelihood ratio statistic is that its value is influenced by the size of the sample, increasing with an increasing number of observations. It can be argued, however, that this feature is perfectly natural as any two models are by definition different and the more observations there are, the more likely it is that the difference, however small, will be picked up. This means that it is necessary to judge the substantive as opposed to the statistical significance of the results; a necessity inherent in the use of any overall measure of fit.

It has been seen, however, when comparing the models containing only level of service variables in Chapter 5, that the other goodness of fit statistics are less influenced by the change in sample size, and although it was difficult to make comparative judgements, they did prove their usefulness. There are however, deficiencies inherent within these measures. In most cases, goodness of fit measures associated with inferential procedures, are to be preferred to those that are merely numbers, and clearly only the Log Likelihood Index escapes such a criticism. Although the "pseudo R^2" statistics do provide an "easy glance" measure of fit, their maximum value is not clearly defined and hence, what constitutes a good fit is somewhat

vague. Further, these statistics are not comparable between models of different functional forms, nor do they provide an intuitive interpretation (comparable to the percentage of variance explained) of goodness of fit.

As a result of these considerations, it is difficult to make judgements on the various goodness of fit measures cited and used in the empirical analysis. They are all functions of $L(\hat{\beta}_0)$ and $L(\hat{\beta}_0 \ldots \hat{\beta}_K)$ and hence, the fact that in the study they generally tend to lead to similar conclusions is not surprising, though it is not inevitable. It is clear that there is no "optimum" goodness of fit statistic to latch on to and in general, the choice of statistic will depend upon how it is to be used.

Another approach to goodness of fit is based on the accuracy of the model in forecasting the observed responses Domencich and McFadden (1975). The simplest measure is the proportion of correctly classified outcomes.

$$PC = \frac{1}{N} \sum_i y_i \delta_i + (1-y_i)(1-\delta_i) \qquad 0 \leq PC \leq 1$$

where $\delta_i = 1$ if $P_i \geq 0.5$

$\delta_i = 0$ if $P_i < 0.5$

If PC took the value of one, it would simply mean that all the observed responses were correctly classified by the model and conversely for PC = 0.

This can be intended to consider the "cost of mis-classification" implying that if an individual chooses an alternative which is not forecast then a cost of mis-classification is incurred. Defining the total cost of mis-classification as

$$C = \sum_i y_i C_1 (1-\delta_i) + (1-y_i) C_2 \delta_i$$

where C_1 is the cost of classifying $y_i = 1$ as 0, and C_2 the cost of classifying $y_i = 0$ as 1.

There are a number of indices of goodness of fit which could be based upon this approach but Domencich and McFadden concentrate on two. Where the cost of mis-classification is proportional to the number of individuals mis-classified $C_1 = 1 = C_2$ and where

$$C_1 = \frac{1}{\bar{P}} \qquad C_2 = \frac{1}{1-\bar{P}}$$

$\bar{P}$ = average probability

In the simple case the proportion of successful forecasts is

$$PS_1 = 1 - \frac{1}{N} \sum_i y_i (1-\delta_i) + (1-y_i)\delta_i$$

with the second case giving a weighted proportion of successful forecasts as

$$PS_2 = 1 - \frac{\sum_i y_i (1-\delta_i)/\bar{P} + (1-y_i)\delta_i / 1-\bar{P}}{\sum_i y_i / 2\bar{P} + (1-y_i)/2(1-\bar{P})}$$

Burns et al (1976) propose a technique which they claim improves the understanding of goodness of fit in the context of probabilistic choice models. This involves forming homogeneous groups of individuals on the basis of the values of the explanatory variable values, to the extent that the main value of the independent variables in the group can be considered representative of all the observations in that cell.

They then use these "representative individual" average values to compute representative probabilities for each group, comparing this predicted probability to the probability given by the proportion of individuals within a given group that choose the alternative. The actual proportion and predicted probabilities are then illustrated in a scatter plot and compared by using R^2, weighted by the number of individuals in each group, calculated for the best linear fit between the measures.

The slope and intercept are computed to illustrate any systematic biases in the model with the significance of the difference between the best linear fit

and the 45° line illustrating complete correspondence being estimated by an F statistic. A number of different ways of defining the groups were tried to test the sensitivity of the results, which they find fairly robust.

These last two approaches were not considered in the study because of their relative computational complexity and the apparent adequacy of the LLR and pseudo R^2 approaches.

APPENDIX 5

IMPLICATIONS OF FUNCTIONAL FORM FOR CONSTANT TERM

In assessing the estimated models of mode choice, it is worthwhile to consider how the constant terms might behave for particular functional forms. Meyburg and Stopher (1975) argue that a non-significant and small constant term is an important property for a model which considers only level of service variables. The reasoning behind this is that if the level of service variables are in difference form and the model is perfectly specified (using just the level of service variables) then a traveller would be indifferent to two modes with identical level of service parameters, and hence his choice probability would be one half and the linear combination of variables would thus need to be zero.

To illustrate consider the model:

$$P_i = \frac{e^{x'\beta}}{1 + e^{x'\beta}}$$

now if $x'\beta = \beta_0 + \beta_1 (CT - BT) + \beta_2 (CC - BC)$

then for identical modes

$$x'\beta = \beta_0$$

as the traveller is indifferent

$$P_i = \frac{1}{2}$$

For $P_i = \frac{1}{2}$ $x'\beta$ must equal 0 which implies

$$\hat{\beta}_0 = 0.$$

By the same reasoning, it can be shown that if the variables are in the relative difference or log of ratios form, the same conditions on the constant form is implied.

However, for the ratio form we have

$$x'\beta = \beta_0 + \beta_1\left(\frac{CT}{BT}\right) + \beta_2\left(\frac{CC}{BC}\right)$$

and for identical models

$$x'\beta = \beta_0 + \beta_1 + \beta_2$$

Now for $P_i = \frac{1}{2}$ we must have $x'\beta = 0$ which implies

$$\beta_0 = -(\beta_1 + \beta_2)$$

Which implies that the constant term will not be zero and in general will be positive as the expected coeff signs on the ratio form of the level of service variables is negative. Thus non-significance of the constant term is no guide to the adequacy of this model form.

The introduction of other variables representing socio-economic factors will, even if the level of service variables enter in the difference form, complicate the analysis of the constant term. This clearly requires dropping the assumption that the model is perfectly specified by the level of service variables and hence there is no reason why when modes are identical the probability of choice should be one half. It is only to be expected that socioeconomic variables will reflect factors that influence mode choice such that even if car and bus were identical as regards their characteristics, the individuals would not be indifferent towards them.

It is possible to argue that if the significance of the constant is reduced by the introduction of a certain variable, the specification has improved. The

reasoning behind this is that, considering

$$x'\beta = \beta_0 + \beta_1 (CT-BT) + \beta_2 (CC-BC)$$

then if β_0 is significant, it implies the model is not a good fit, reflecting the mis-specification and making $x'\beta = 0$ when the modes are identical. Introducing a socio-economic variable

$$x'\beta = \beta_0 + \beta_1 (CT-BT) + \beta_2 (CC-BC) + \beta_3 S$$

then if the modes are identical

$$x'\beta = \beta_0 + \beta_3 S$$

If β_3 **is positive** and significant and has reduced the significance of a positive β_0, it might be argued that it is taking up some of the effect of β_0 which reflected the required deviation from achieving $P_i = \frac{1}{2}$ when $x'\beta = 0$; and analogously for negative.

If β_3 and β_0 have differing signs, β_0 will be increased and thus might tentatively be argued to be worsening the model. However, for such a conclusion to be reached, it would be necessary to assume CT-BT and CC-BC picked up all of the level of service effects, and in practice they obviously do not. As further variables are introduced the analysis becomes much more complex and standing on shaky ground as it does, not really worthwhile. Especially when one regards the stringent assumptions required to validate the analysis.

APPENDIX 6

NON-CONVERGENCE

The major reason for non-convergence in the logit model is that the explanatory variable takes a particular value everytime the dependent event occurs (i.e. takes the value 1). The dependent variable could take the value of 1, when the explanatory variable does not take the particular values, as long as it always takes the value 1 when the explanatory variables takes this particular value. This will clearly affect the estimation of the coefficients in a probability function as the sample data would imply that the probability of the dependent variable taking the value 1 must be unity when the explanatory variables takes its particular value.

Then

$$P_i(y=1) = \frac{e^{x_i'\beta}}{1+e^{x_i'\beta}} = 1$$

Consider

$$x'\beta = \alpha_0 + \beta_1 x_i$$

then

$$\alpha_0 + \beta_1 x_1 = \log\left[\frac{P_i(y=1)}{1-P_i(y=1)}\right] = \log\left(\frac{1}{0}\right)$$

$$\Rightarrow \quad \alpha_0 + \beta_1 x_1 = \infty$$

hence

$$\beta_1 \longrightarrow \infty$$

Thus if the probability must be unity for the explanatory variable to take a particular value then the estimated coefficient must be infinite. Thus the program used in estimation will not be able to handle a number that large and will fail to converge. It is possible that it might converge with a large number of iterations but this will result in strange values for the coefficient estimate and the constant term.

The constant terms will generally be affected when one of the coefficients takes a large positive or negative value as it will try to compensate for this and allow the probability function to take reasonable values for the remaining explanatory variables coefficients. Thus, the affected explanatory variable will move together with the constant, but with differing signs, through successive iterations.

It is worth noting that the probability of one need not and generally will not be the same for the whole population. So it is more likely that this problem, of non-convergence, will occur with small or peculiar samples, or with variables containing only information for one of the choices.

It is possible for non-convergence to arise with continuous variables if the dependent variable always or never occurs when the independent variable has values within a specific range. Further, it is possible that linear combination of variables may display the same effect.

Nerlove and Press (1973) note that this signal of an extreme low or high coefficient and hence non-convergence, will not be shared by the linear probability model. They regard this fact as a shortcoming of the linear probability rather than an advantage.

The solution to the problem of non-convergence is to partition the sample by the explanatory variable that is causing it and then to re-estimate the model conditional on the value of this variable over the sample. Clearly we know the probability of the dependent eventoccuring is high when the explanatory

variable takes a particular value (or range of values), but the data does not provide information on how high. The converse holding for low probabilities.

When the problem involves lack of information of alternative specific variables for the non-chosen alternative (as with the available parking information in the study) such partitioning is not practical as it would involve partitioning by mode, which is clearly nonsensical in a mode choice study. In such a case, non-convergence is caused by the mode specific quality of the variable rather than the values of the variable.

APPENDIX 7

COMPARISON OF TOTAL SAMPLE WITH SUB-SAMPLE OF HOUSEHOLDS WITH MORE THAN ONE WORKER IN EDINBURGH.

Although the study is based upon the individual commuter as the decision unit, it is worthwhile to consider the households to which the individual's belong. Comparing the characteristics of the households which contain Edinburgh commuters with the total sample of households yields some interesting results as regards the social background of the commuters.

It is worth noting that the value of this comparison lies in a deficiency of this study. The random sample upon which the survey was based, was a sample of households. Thus, to use the individual's as the unit of analysis is sub-optimal, in that the sample of individuals is a cluster sample; the clusters being the households and hence not random.

The social class of the household which is registered as the social class of the head of household (as is usual) would appear to describe the greatest discrepancy between the two sets of households. The households with at least one worker in Edinburgh (WIE) appears to be concentrated in the high social class groups, with the WIE group having 50% of households in the top 3 groups while only 34.3% for the total sample (TS).

There is also a much smaller proportion of retired persons 1.8% when compared with the total sample (7.2) and a larger proportion of students, which is to be expected with the Universities in Edinburgh.

The socio-economic grouping illustrates the same features with the WIE having higher proportions in the top 7 socio-economic groups, reflecting the professional and service employment that is available in Edinburgh.

The proportion of households in the WIE sample from each district was not markedly different from those of the total sample (TS), the main discrepancy being in Deans which had an 11.2% representation in the WIE

sample. This probably results from Deans being one of the oldest parts of the town and its having taken in workers from the Bathgate BL plant together with the initial populations of Deans village.

In contrast Murieston shows higher representation of households in the WIE sample (9.5%) than in the total sample (6.2%). This probably relates to the level of private housing in this district implying higher social class households with the increased possibility of commuting to service work in Edinburgh. The other districts are within 2% either way.

Household size distribution is again similar for both samples although the total sample contains a higher proportion of single person households (9.3) than the WIE sample (3.6). This will reflect the fact that older, retired people are unlikely to commute to Edinburgh while young professional people are. There are also about 6% more 2-person households in the WIE sample reflecting the greater mobility of childless couples.

The centre of the household size distribution is similar for both samples, though the larger families tend to have a smaller representation in the WIE sample, again relating to the lower social grouping of larger families and their constraints on mobility.

As regards employment within the households, the WIE sample has a much smaller proportion of households without any members in employment (2.3) than the total sample. This will reflect the non-inclusion of pensioners and retired persons in the WIE sample, but will also relate to the higher social status of the WIE households. A further important consideration is the greater mobility of the WIE households, in that household members may commute to Edinburgh to work rather than remain unemployed.

That the WIE sample contains a smaller proportion of households with only one full time employed member (52%:59%) and a larger proportion of households with 2 full time employed members, would again seem to imply

the social class and occupational differences between the groups, and the incidence of working spouses which is underlined by the higher part-time employed proportion of the WIE sample.

The smaller household size of the WIE sample is further reflected in the smaller numbers of children and dependents, with the smaller proportion of no dependents reflecting the smaller proportion of retired people and pensioners. There is also a greater proportion of 1 child families (23.1%) in the WIE sample than the total sample (17.5%) further illustrating the higher social standard young professional nature of households with a worker in Edinburgh.

The WIE sample had a much higher level of car ownership than the total sample with 77.4% using at least one car in constrast to 61.0% in the total sample. This compared with a national (GB) average of 56% shows Livingston to have a surprisingly high level of car ownership, more surprising when the Scottish car ownership levels are generally low in comparison to the GB average. The higher car ownership levels of the WIE sample relates to the higher social class of the households and possibly the distance involved in the work trip to Edinburgh, making a car a more likely purchase than if purely internal commuting. The social class effect further illustrated by the higher proportion of $\geqslant$ 2 car families 10% compared with 5.9% in the total sample.

As regards the individuals in the households in the WIE sample it must be remembered that all individuals who are in a household where at least one of the members works in Edinburgh are included, hence the figures reflect different characteristics than a sample of individual commuters to Edinburgh. The sex and employment status of the individuals in the WIE showed a lower proportion of male full-time employed (66:61%) but a higher proportion of female full-time employed (24:27%). This might be regarded as implying a larger proportion of working wives, underlined by the larger proportion of female FT who are second employed and relating to higher

social class young professional household structures. The differences in male and female employment in Edinburgh reflects the form of available employment in Edinburgh, namely professional and service.

APPENDIX 8

MAXIMUM LIKELIHOOD ESTIMATION

This appendix outlines the approach used in the computer programs to provide the maximum likelihood estimates of the model parameters. For simplicity, the binary logit is used but the method is easily generalised.

Following on from Chapter 4, the likelihood function for the binary logit model can be written

$$L = \prod_{i=1}^{N} P_i^{y_i} \left(1-P_i\right)^{1-y_i}$$

which gives

$$\log L = L^* = \sum_{i=1}^{N} (\log P_i)\, y_i + \sum_{i=1}^{N} \log (1-P_i)\,(1-y_i)$$

$$= \sum_{i=1}^{N} \log\left(\frac{e^{x_i'\beta}}{1+e^{x_i'\beta}}\right) y_i + \sum_{i=1}^{N} \log\left(1-\frac{e^{x_i'\beta}}{1+e^{x_i'\beta}}\right)(1-y_i)$$

expanding this function

$$L^* = \sum_i y_i \left[\log e^{x_i'\beta} - \log\left(1+e^{x_i'\beta}\right)\right] + \sum_i (1-y_i) \log\left(\frac{1}{1+e^{x_i'\beta}}\right)$$

$$= \sum_i y_i (x_i'\beta) - \sum_i y_i \log\left(1+e^{x_i'\beta}\right) - \sum_i \log\left(1+e^{x_i'\beta}\right) + \sum_i y_i \log\left(1+e^{x_i'\beta}\right)$$

$$= \sum_i y_i (x_i'\beta) - \sum_i \log\left(1+e^{x_i'\beta}\right)$$

Now the MLE's of the coefficients will be those values where the log likelihood function's value is at a maximum. Thus the implied conditions for N individuals i = 1,....N and K variables k = 1,...,K.

$$\frac{\delta L^*}{\delta \beta_k} = \sum_i y_{ik} x_{ik}$$

$$= \sum_i y_i x_{ik}$$

These K equations are non-linear in the parameters but can be solved using an iterative procedure, such as the Newton Raphson method [1].

If we take

$$\frac{\delta L^*}{\delta \beta_k}(\hat{\beta}) = 0$$

as the condition for maximum with $\hat{\beta}$ being the MLE's of the coefficients with the 1st derivative of L* evaluated at $\hat{\beta}$. Then taking a Taylor expansion

$$0 = \frac{\delta L^*}{\delta \beta_k}(\hat{\beta}) = \frac{\delta L^*}{\delta \beta_k}(\bar{\beta}) + \sum_l \Delta \beta_k \frac{\delta L^*}{\delta \beta_k \beta_l}(\bar{\beta}) + \ldots$$

ignoring higher order terms this implies $(\bar{\beta}$ = trial values$)$

$$\Delta \beta_k = -\frac{\delta L^*}{\delta \beta_k}(\bar{\beta}) \left[\sum_l \frac{\delta L^*(\bar{\beta})}{\delta \beta_l \beta_k} \right]^{-1}$$

1. **Maddala (1977) and Goldfeld and Quandt (1972) present this and other available procedures.**

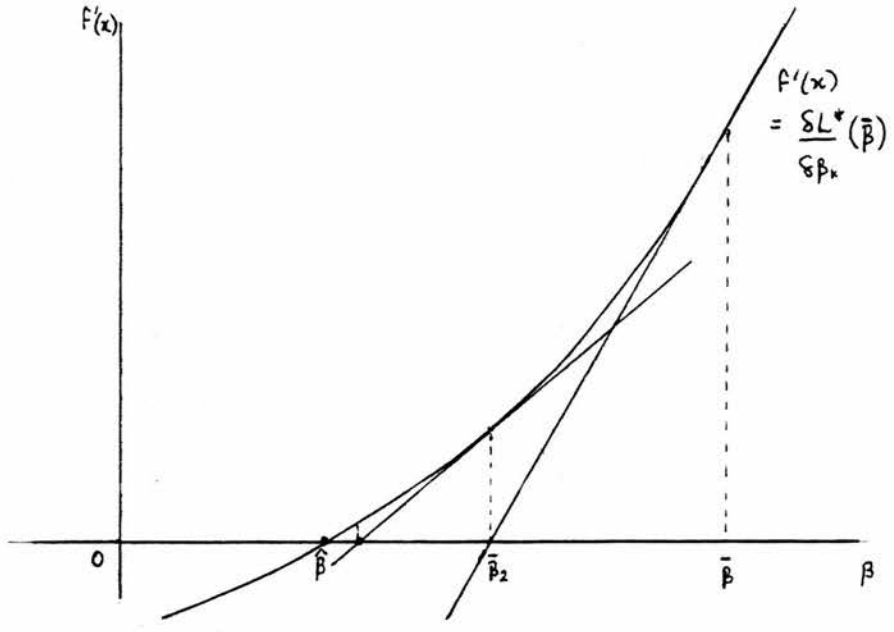
This, thus, is the adjustment to the trial values which will bring $\frac{\delta L^*(\bar{\beta})}{\delta \beta_k}$ closer to zero and hence to $\frac{\delta L^*(\hat{\beta})}{\delta \beta_k}$

The second order conditions can be derived:

$$\frac{\delta L^*}{\delta \beta_k \beta_l} = - \frac{\sum_i x_{ik}(1+e^{x_i'\beta})e^{x_i'\beta} x_{il} - [e^{x_i'\beta}]^2 x_{ik} x_{il}}{(1+e^{x_i'\beta})^2}$$

$$= - \sum_i x_{ik} x_{il} \frac{e^{x_i'\beta}}{(1+e^{x_i'\beta})^2}$$

To illustrate the approach consider a model with only one parameter:



Starting at an initial value $\bar{\beta}$ f'(x) is evaluated and a tangent dropped from that point on the curve. Where this tangent cuts the β axis determines the

new trial values $\bar{\beta}_2$, hence an increment of $\bar{\beta}_2 - \beta$. This procedure is then continued until convergence to $\hat{\beta}$ and $f'(x) = 0$.

Alternatively one could simply compute linear adjustments $\Delta\beta_K$ assuming $\delta L/\delta\beta_K$ is linear between the trial value and the real solution [DeDonnea (1971)].

This implies

$$\frac{\delta L}{\delta \beta_k}\left(\bar{\beta}_1+\Delta\beta_1, \ldots, \bar{\beta}_K+\Delta\beta_k\right) = \frac{\delta L}{\delta \beta_k}(\bar{\beta}) + \sum_{\ell} \frac{\delta L}{\delta \beta_k \beta_\ell}(\bar{\beta}) \cdot \Delta\beta$$

$$= 0$$

$$\Rightarrow \qquad \Delta\beta = -\frac{\delta L}{\delta \beta_k}(\bar{\beta}) \cdot \left[\sum_{\ell} \frac{\delta L}{\delta \beta_k \beta_\ell}(\bar{\beta})\right]^{-1}$$

The negative of the inverse of the matrix $\delta L^*/\delta\beta_K\beta_\ell$ evaluated at the MLE's of β provides a good estimate of the assymptotic variance covariance matrix for the parameter estimates.

Although there are other, and more complex approaches (algorithms) for finding the MLE's, in the study the Newton-Raphson approach converged quickly and consistently from zero starting values. This, together with the uniqueness of the estimates obtained [McFadden (1973)] implied that the Newton-Raphson approach was adequate for this study.

APPENDIX 9

PROOF OF INCREMENTAL LOGIT

Consider binary logit of the form

$$P_i = \frac{e^{x_i'\beta}}{1+e^{x_i\beta}}$$

then for a change in x_i for all individuals

$$\tilde{x}_i\beta = x_i'\beta + \beta_k \Delta x_{ki}$$
$$= \phi_i + \Delta\phi_i$$

Writing in this form

$$P_i = \frac{e^{\phi_i+\Delta\phi_i}}{1+e^{\phi_i+\Delta\phi_i}}$$

$$= \frac{e^{\phi_i}e^{\Delta\phi_i}}{1+e^{\phi_i}e^{\Delta\phi_i}}$$

Dividing top and bottom by $1+e^{\phi_i}$

$$P_i' = \frac{e^{\phi_i}e^{\Delta\phi_i}/1+e^{\phi_i}}{(1+e^{\phi_i}e^{\Delta\phi_i})/1+e^{\phi_i}}$$

which implies

$$P_i' = \frac{P_i e^{\Delta\phi_i}}{(1/1+e^{\phi_i})+P_i e^{\Delta\phi_i}}$$

now $$\frac{1}{1+e^{\Phi_i}} = 1 - \frac{e^{\Phi_i}}{1+e^{\Phi_i}} = 1 - P_i$$

Hence

$$P_i' = \frac{P_i e^{\Delta\Phi_i}}{(1-P_i) + P_i e^{\Delta\Phi_i}}$$

dividing top and bottom by P_i

$$P_i' = \frac{e^{\Delta\Phi_i}}{C_i + P_i e^{\Delta\Phi_i}}$$

where $C_i = [(1-P_i)/P_i]$

Thus it is possible to model the effects of change in explanatory variables without reestimation of the whole model. For extension and application to MNL see Ben-Akiva and Atherton (1977).

APPENDIX 10

PROOF OF ARC ELASITICITY APPROXIMATION

The formula for the arc elasticity presented in Chapter 9:

$$E_\ell = \frac{\Delta \bar{P}}{\Delta \bar{x}_\ell} \cdot \frac{2\bar{x}_\ell + \Delta \bar{x}_\ell}{2\bar{P} + \Delta \bar{P}}$$

From the point elasticity for a uniform absolute change in Chapter 9:

$$\frac{\delta \bar{P}}{\delta \bar{x}_\ell} \cdot \frac{\bar{x}}{\bar{P}} = \frac{\sum_i P_i(1-P_i)\beta_\ell \bar{x}_\ell}{\sum_i P_i}$$

which can be written as

$$\frac{\delta \bar{P}}{\delta \bar{x}_\ell} = \frac{\sum_i P_i(1-P_i)\beta_\ell \bar{x}_\ell}{\bar{x}_\ell \sum_i P_i}$$

multiplying top and bottom by 1/N and cancelling gives

$$\frac{\delta \bar{P}}{\delta \bar{x}_\ell} = \frac{1}{N} \cdot \sum_i P_i(1-P_i)\beta_\ell$$

Now if the approximation

$$\frac{\delta \bar{P}}{\delta \bar{x}_\ell} \approx \frac{\Delta \bar{P}}{\Delta \bar{x}_\ell}$$

is made then arc elasticity can be written as

$$E_\ell \approx \frac{1}{N} \sum_i P_i (1-P_i) \beta_\ell \cdot \frac{2\bar{x}_\ell + \Delta \bar{x}_\ell}{2\bar{P} + \Delta \bar{P}}$$

$$= \frac{\sum_i P_i (1-P_i) \beta_\ell \left(2\bar{x}_\ell + \Delta \bar{x}_\ell\right)}{2 \sum_i P_i + \sum_i P_i (1-P_i) \beta_\ell \Delta \bar{x}_\ell}$$

which is the approximate arc elasticity for equal absolute changes used in the study. Alternatively if the point elasticity formula for equal proportion changes is used this implies:

$$\frac{\delta \bar{P}}{\delta \bar{x}_\ell} = \frac{\bar{P} \beta_\ell \sum_i P_i (1-P_i) x_{i\ell}}{\bar{x}_\ell \sum_i P_i}$$

$$= \frac{\beta_\ell \sum_i P_i (1-P_i) x_{i\ell}}{\sum_i x_{i\ell}}$$

which gives the arc elasticity:

$$E_\ell = \frac{\beta_\ell \sum_i P_i(1-P_i)x_{i\ell}(2\bar{x}_\ell + \Delta\bar{x}_\ell)}{2\bar{P}\sum x_{i\ell} + \beta_\ell \sum_i P_i(1-P_i)x_{i\ell}\Delta\bar{x}_\ell}$$

APPENDIX 11

BINARY LOGIT COMPUTER PROGRAM

This appendix presents the purpose written binary logit computer program used in the empirical analyses. The programs are written in Fortran IV and are compatible with the Edinburgh Multi Access System (EMAS).

To run the compiled binary logit program the following specifications for input and output streams are required:

DEFINE (1, DATA) input data from file data
DEFINE (6, .LP?) output results to line printer no.?
DEFINE (7, .LP?) output graphs to line printer no.?
DEFINE (2, .IN) input variable and task selection parameter through terminal
or DEFINE (2, INPUT) input variable and task selection parameter from file INPUT
RUN (BNL 1) run BNL1 the compiled version of the binary logit program (object file).

The data used for the program is input in the format specified in format statement 1ØØ in the main program. If channel 2 is defined as the terminal then when the program is running the user will be prompted Data: and the required parameters should be input in the order and format outlined. If channel 2 is defined as a file then the relevant file should contain the parameters in the same order and format. The maximum number of variables is 12 and the maximum number of observations 400, although both can be easily increased by changing the dimension statements.

The following stages are required to provide the sample and model specification for a particular run. Each are either the response to prompts if running the program at the VDU or the consecutive lines of a file defined on channel 2.

1. Provide the relevant information for the run, specifying the number of variables (format I2)*, the number of observations (I2) and the required sample(I1)

   The required samples are fixed at Ø for the total sample, 1 for car available sample, 2 for heads sample.

2. Provide the relevant variable specification parameters listing the variable numbers on a separate line for each run. The number of variables specified being the same as stated in the stage above. If it is not required to make the first four variable into differences then a zero should precede the variable numbers. Any number of runs can be specified thus and when either termination or a change in specifications of stage one are required then 4 zeros should be typed on a separate line and then in response to the next prompt either:

   1. stages one and two can be repeated for the new specification

   or 2. Ø can be typed in and the program run will be terminated.

This form of the program is such that it is specific to the study in its variable and sample specifications. The various subroutines are however, self consistent. This means that they can be employed from different main programs as long as the data is in the form presented. For the study the value 13 represented a missing value and the dependent variable was computed in the subroutine OAVARS.

*** ie. the number of variables being input at the variable specification (2nd stage). This will not necessarily be the final number of variables as using differences means creating composite variables.**

From line 92 the main program can be changed depending upon the results, and hence the subroutines, required. The subroutines are a number of external routines. Routines from the Nag Library FØ1AAF and DØ1GAF are for matrix inversion and numerical integration, respectively, and IMPGRAPH9 a routine to supply line printer graphs which is available on the Edinburgh system. If IMPGRAPH is not available then the calls to the routine within the subroutines need to be cancelled.

```
C
C
C    MAIN PROGRAM WITH VARIABLE SELECTION ROUTINE
C    GENERALISED CHOICE OF VARIABLE AND SAMPLE SELECTION
C
C
C
C     THIS PROG IS BINARY LOGIT WITH SIMULATION PROCEDURES
C    REQUIRES DEFINE(1,FINDAT4),(6,.LP?),(7,.LP?)
C  DEFINE(2,.IN OR FILE WITH INPUT)
C   NO.VARS(I2), NO. OBS(I3), SAMPLE(I1)
C    CHOSEN VARS UP TO 12(12I2)
C
      REAL*8 EXPLAN(400,12),ALIKE(12),LIKE,BLIKE,CLIKE,CHANG(12),
     * BDERV1(12),DERV2(12,12),DERV1(12),B(12),PROB1,PROB2,
     * LCV,EXPLCV,DINVD2(12,12),COVAR(12,12),STEP(12),TVAL,UPPER,LOWER,
     * SUMY,SUMYN,LLRA,LLR,PSQ,PSQQ,PSQK,LIKEN,APSQ,PRS,SY(400),
     * Y(400),X(60),WKPCE(25),ELPROB(400),ASB1(41),ASB2(41),
     *AASB(6,41),BASB(6,41),
     *VARCOV(12,12),AVX(12),AVXB,AVP,AP(41),ASB(41),VARXB,PSUM,AVPR,ANC
C
      INTEGER IV(15),IVA(100,15)
C
      COMMON/VCOM/EXPLAN,PSUM,SY,SUMY,X,IVA,IV,N
      COMMON/GR/IGRN
      EQUIVALENCE (SY(1),Y(1))
C
      WRITE(6,300)
  300 FORMAT(/1X,'BINARY LOGIT ESTIMATION WITH SIMULATIONS ',//
     *,1X,'PROG=BNLSIM DATA=FINDAT4')
C
C  READ IN RELEVANT INFO FOR RUN
  301 FORMAT(I2,I3,I1)
  997 READ(2,301)(IV(K),K=1,3)
      IF (IV(1).EQ.0) GOTO 999
      L2=IV(1)
      L1=L2-1
      L=L2-1
      M=IV(2)
C
      DO 4 IA=1,100
      IGRN=0
      READ(2,302)(IVA(IA,K),K=1,L2)
  302 FORMAT(12I2)
C
      IVVA=IVA(IA,1)+IVA(IA,2)
      IF(IVVA.EQ.0) GOTO 998
C
      WRITE(6,303)(IV(K),K=1,3),(IVA(IA,K),K=1,L2)
  303 FORMAT('1',/,1X,'NO. VARIABLES=',I4,1X,'NO. OBSERVATIONS=',I6,2X,
     * /,1X,'SAMPLE NO.=',I4,4X,'0=TOT SAMPLE: 1=CAR AVAIL SAMPLE:
     *  2=HEADS SAMPLE',/,1X,'VARIABLES USED= CONSTANT',1X,12I4)
C   INITIALISE
C
C    IF IVA(IA,1) IS ZERO THEN VARIABLES ARE NOT DIFFS
C
      IF(IVA(IA,1).EQ.0) L=L2
C
      DO 2 K=1,L1
      B(K)=0.0
```

```
      DO 2 K1=1,M
    2 EXPLAN(K1,K)=0.0
      ITER=0
      SUMY=0
      MM=0
      N=0
      DO 3 K=1,60
    3 X(K)=0.0
C
C   READ IN DATA, ASSIGN VARIABLES USING SUBROUTINE VARS
C   DELETE CASES WITH MISSING VALUES
C
      REWIND 1
      DO 1 I=1,M
      MM=MM+1
      READ(1,100) X
    1 CALL OAVARS(MM,L2,IA)
  100 FORMAT(F3.0,7F2.0,2F3.2,30F2.0,F3.0,5F2.0,2F3.0,F2.0,F3.1,10F5.2)
C
      WRITE(6,199) N
  199 FORMAT(1X,'NO OF CASES WITHOUT MISSING VALUES',1X,I4)
C
C      WRITE(6,197)
C      DO 25 K1=1,30
C   25 WRITE(6,198) Y(K1),(EXPLAN(K1,K2),K2=1,L)
  197 FORMAT(/1X,' Y VALUES AND EXPLAN VARS')
  198 FORMAT(2X,12F10.3)
C
C
C
C
      CALL SMBBNL(ELPROB,B,L,IA)
C
      CALL SMVCOV(EXPLAN,L,N,B,VARCOV,AVX,AVXB,VARXB)
C
      CALL SMEL(EXPLAN,B,ELPROB,SUMY,L,N)
C
      CALL SMCMC(ELPROB,Y,L,N)
C
      CALL SMTALV(B,VARCOV,ELPROB,AVX,L,N)
C
      CALL SSBD(AVXB,VARXB,AVX,ELPROB,AP,ASB,B,L,N,1)
C
      CALL CLASS(EXPLAN,B,L,N)
CC
C
C
      ILL=0
      IAA=0
      IP=4
      IF(IV(1).LE.4)IP=3
      DO 10 IVV=2,IP
      ANC=-10.0
      IB=0
      WRITE(6,200) IVV
  200 FORMAT('1',//,1X,'**************VARIABLE',2X,I2,2X,'SIMULATION')
      DO 11 II=1,5
      IF(ANC.EQ.0) GOTO 11
      IB=IB+1
```

```
C
      CALL SIMSB(ELPROB,AVX,AVXB,B,VARXB,ASB,ASB1,AP,L,N,IVV,ANC,IAA,1)
C
      CALL RESIM(EXPLAN,B,ELPROB,ASB,ASB2,L,N,IVV,ANC,IAA,1)
C
      CALL PINC(ELPROB,EXPLAN,B,AVX,N,L,IVV,ANC,IAA)
C
C      DO 12 K=1,41
C      AASB(IB,K)=ASB1(K)
C   12 BASB(IB,K)=ASB2(K)
C
   11 ANC=ANC+5.0
C
C      IL=5
C      CALL SBSIL(ASB,AASB,AP,IL)
C      CALL SBSIL(ASB,BASB,AP,IL)
C
   10 CONTINUE
C
    4 CONTINUE
C
  998 GO TO 997
C
  999 STOP
      END
C
C
C
C
```

```
      SUBROUTINE DAVARS(M,L,IA)
C
C     THIS ROUTINE SELECTS REQUIRED SAMPLE, ASSIGNS CHOSEN VARIABLES
C     AND DELETES CASES WITH MISSING VALUES
C
      INTEGER IV(15),IVA(100,15)
      REAL*8 X(60),EXPLAN(400,12),AVAR(400,12),SY(400),SUMY,PSUM
      COMMON/VCOM/EXPLAN,PSUM,SY,SUMY,X,IVA,IV,N
C
      ST=X(15)
      NCR=X(8)
C
C
C  CHECK IF CAR AVAIL SAMPLE
        IF(IV(3).EQ.1) GOTO 2
C   CHECK IF HEADS SAMPLE
        IF(IV(3).EQ.2) GOTO 3
C    CHECK IF  NOT CAR AVAILABLE
        IF(IV(3).EQ.3) GOTO 10
C   CHECK IF NOT HEADS
        IF(IV(3).EQ.4) GOTO 11
        GOTO 4
C
    2 IF(NCR.EQ.13) GO TO 1
        IF(NCR.LT.1) GOTO 1
         GOTO 4
C
    3 IF(ST.GT.1.5) GOTO 1
        GOTO 4
C
   10 IF(NCR.EQ.13) GOTO 1
        IF(NCR.GE.1.0) GOTO 1
        GO TO 4
C
   11 IF(ST.EQ.13) GOTO 1
        IF(ST.LT.1.5) GOTO 1
C
    4 CONTINUE
C
      IF(IVA(IA,1).EQ.0) GOTO 15
C
C
C   ASSIGN EXPLAN VARS
C
      AVAR(M,1)=1.0
      LL=L+1
      DO 5 K=1,L
    5 AVAR(M,K+1)=X(IVA(IA,K))
C
      IF(LL.LT.6) GO TO 8
C
      IF(X(20).EQ.13) GO TO 1
      DO 6 K=6,LL
      IF(AVAR(M,K).EQ.13) GOTO 1
    6 CONTINUE
C
    8 N=N+1
      SY(N)=0
      IF(X(20).EQ.5) SY(N)=1.0
      IF(X(20).EQ.6) SY(N)=1.0
```

```
      SUMY=SUMY+SY(N)
C
      EXPLAN(N,1)=AVAR(M,1)
      EXPLAN(N,2)=AVAR(M,2)-AVAR(M,3)
      EXPLAN(N,3)=AVAR(M,4)-AVAR(M,5)
      LP=LL-2
C
      IF(LP.LT.4) GO TO 1
C
      DO 7 K=4,LP
      KK=K+2
    7 EXPLAN(N,K)=AVAR(M,KK)
C
      GOTO 1
   15 CONTINUE
C
      IF(X(20).EQ.13) GOTO 1
      AVAR(M,1)=1.0
      DO 12 K=2,L
      AVAR(M,K)=X(IVA(IA,K))
      IF(AVAR(M,K).EQ.13) GOTO 1
   12 CONTINUE
C
      N=N+1
      SY(N)=0
      IF(X(20).EQ.5) SY(N)=1.0
      IF(X(20).EQ.6) SY(N)=1.0
      SUMY= SUMY+SY(N)
      DO 13 K=1,L
   13 EXPLAN(N,K)=AVAR(M,K)
C
    1 RETURN
      END
C
```

```
      SUBROUTINE SMBBNL(ELPROB,B,L,IA)
C
C     THIS ROUTINE COMPUTES MAXIMUM LIKLIEHOOD ESTIMATES FOR THE
C     BINARY LOGIT MODEL USING NEWTON-RALPHSON METHOD
C      IT ALSO PRODUCES VARIOUS GOF STATS
C
      REAL*8 EXPLAN(400,12),ALIKE(12),LIKE,BLIKE,CLIKE,CHANG(12),
     * BDERV1(12),DERV2(12,12),DERV1(12),B(12),PROB1,PROB2,
     * LCV,EXPLCV,DINVD2(12,12),COVAR(12,12),STEP(12),TVAL,UPPER,LOWER,
     * SUMY,SUMYN,LLRA,LLR,PSQ,PSQQ,PSQK,LIKEN,APSQ,PRS,SY(400),
     * Y(400),X(60),WKPCE(25),ELPROB(400),
     *VARCOV(12,12),AVX(12),AVXB,AVP,AP(26),ASB(26),VARXB,PSUM
C
      INTEGER IV(15),IVA(100,15)
C
      COMMON/VCOM/EXPLAN,PSUM,SY,SUMY,X,IVA,IV,N
      EQUIVALENCE (SY(1),Y(1))
C
C
C
      DO 2 K=1,L
    2 B(K)=0.0
      ITER=0
      PSUM=0
C
C
C
C
  101 FORMAT(/1X,' ITERATION NO=',1X,I10)
  102 FORMAT(/1X,' CURRENT VAL LIKE FUNC=',1X,F20.15)
  103 FORMAT(/1X,' MATRIX OF 2ND ORDER DERIVS')
  104 FORMAT(/1X,' VECTOR OF 1ST ORDER DERIVS'/(1X,F15.9))
  105 FORMAT(/1X,' NO CHANGED VALS OF 1ST DERIVS=',1X,I6)
  106 FORMAT(/1X,' CURRENT B VALUES'/(5X,F15.5))
  107 FORMAT(/1X,' M.L.E''S='/(1X,F15.5))
  108 FORMAT(/1X,' INVERSE OF DERV2 ')
  109 FORMAT(/1X,' VAR-COVAR MATRIX ')
  110 FORMAT(/1X,'T-STATISTIC=',1X,F15.3,2X,'MLE',1X,F10.3)
  111 FORMAT(/1X,' S.E.S OF B='/(12X,F9.5))
  112 FORMAT(/1X,' NO ITERATIONS FOR MLES=',1X,I6)
  113 FORMAT('1',/1X,'NO VARS=',1X,I2,2X,'NO OBS=',1X,I4,2X,
     *'VARIABLES USED= CONST',1X,I4,'-',I4,2X,I4,'-',I4,1X,10I4)
C
   10 CONTINUE
      CLIKE=0.0
      PSUM=0
      BLIKE=0.0
      DO 19 K=1,L
      CHANG(K)=0
   19 CONTINUE
      ITER=ITER+1
      NCHANG=0
      DO 5 K=1,L
      ALIKE(K)=0.0
      BDERV1(K)=0.0
    5 CONTINUE
      DO 6 K1=1,L
      DO 6 K2=1,L
    6 DERV2(K1,K2)=0.0
      DO 20 I=1,N
```

```
      LCV=0.0
      DO 21 K=1,L
   21 ALIKE(K)=ALIKE(K)+Y(I)*EXPLAN(I,K)
      DO 22 K=1,L
   22 LCV=LCV+EXPLAN(I,K)*B(K)
      EXPLCV=DEXP(LCV)
      BLIKE=BLIKE+DLOG(1+EXPLCV)
      PROB1=EXPLCV/(1+EXPLCV)
      PROB2=EXPLCV/(1+EXPLCV)**2
      ELPROB(I)=PROB1
      PSUM=PSUM+PROB1
      DO 23 K1=1,L
      DO 23 K2=1,L
   23 DERV2(K1,K2)=DERV2(K1,K2)-EXPLAN(I,K1)*EXPLAN(I,K2)*PROB2
      DO 24 K=1,L
   24 BDERV1(K)=BDERV1(K)+EXPLAN(I,K)*PROB1
   20 CONTINUE
C  150 FORMAT(/1X,'INDIV PROBS=',1X,F8.5)
C
      DO 30 K=1,L
   30 CLIKE=CLIKE+ALIKE(K)*B(K)
      LIKE=CLIKE-BLIKE
      WRITE(6,101)ITER
      WRITE(6,102)LIKE
      DO 31 K=1,L
   31 DERV1(K)=ALIKE(K)-BDERV1(K)
C      WRITE(6,103)
C      DO 7 K2=1,L
C    7 WRITE(6,135)(DERV2(K1,K2),K1=1,L)
  135 FORMAT(2X,12F9.3)
      WRITE(6,104)(DERV1(K),K=1,L)
      ID=12
      NA=L
      IVV=12
      IFAIL=0
      CALL F01AAF(DERV2,ID,NA,DINVD2,IVV,WKPCE,IFAIL)
      IF(IFAIL.EQ.1) GOTO 4
      DO 40 K1=1,L
      DO 40 K2=1,L
   40 CHANG(K1)=CHANG(K1)+DINVD2(K1,K2)*DERV1(K2)
      DO 41 K=1,L
      B(K)=B(K)-CHANG(K)
      IF(DABS(DERV1(K)).GE.0.0000000005)NCHANG=NCHANG+1
   41 CONTINUE
      WRITE(6,105) NCHANG
      IF(NCHANG.EQ.0) GOTO 50
      WRITE(6,106)(B(K),K=1,L)
      IF(ITER.EQ.25) GO TO 4
      GO TO 10
C
C
C
C
C
C
   50 WRITE(6,107)(B(K),K=1,L)
C
      AVP=PSUM/N
C
```

```
      L2=L+1
C      WRITE(6,113)IV(1),N,(IVA(IA,K),K=1,L2)
C      WRITE(6,108)
C      DO 8 K2=1,L
C    8 WRITE(6,144)(DINVD2(K1,K2),K1=1,L)
  144 FORMAT(2X,12F9.3)
C
      DO 51 K1=1,L
      DO 51 K2=1,L
   51 COVAR(K1,K2)=-DINVD2(K1,K2)
      WRITE(6,109)
      DO 9 K2=1,L
    9 WRITE(6,144)(COVAR(K1,K2),K1=1,L)
      WRITE(6,107) (B(K),K=1,L)
      DO 60 K=1,L
      STEP(K)=DSQRT(COVAR(K,K))
C      UPPER=B(K)+1.96*STEP(K)
C      LOWER=B(K)-1.96*STEP(K)
      TVAL=B(K)/STEP(K)
      WRITE(6,110)TVAL,B(K)
   60 CONTINUE
      WRITE(6,111)(STEP(K),K=1,L)
      WRITE(6,112)ITER
C
C
C
      L1=L-1
      SUMYN=SUMY/N
      LLRA=SUMY*DLOG(SUMYN)+(N-SUMY)*DLOG(1-SUMYN)
      LLR=(-2)*(LLRA-LIKE)
      WRITE(6,116) LLR,L1
      PSQ=1-(LIKE/LLRA)
      PSQQ=1-PSQ
      PSQK=(L/L1)*(PSQ/PSQQ)
      WRITE(6,117) PSQ
      WRITE(6,118) PSQK,L1,L
      LIKEN=LIKE*N
      LM1=N-L
      APSQ=1-(LIKEN/(LLRA*LM1))
      WRITE(6,115)APSQ
      PRS=1-(DEXP((LIKE-LLRA)*(-2.0/N)))
      WRITE(6,142)PRS
  114 FORMAT(/1X,'NO. RELEVANT CASES-WITHOUT MISSING VALUES=',1X,I3)
  116 FORMAT(/1X,'LOG-LIKE RATIO=',1X,F12.5,3X,'CHI-SQUARED DOF=',1X,I3)
  117 FORMAT(/1X,'P-SQUARED=',1X,F5.3)
  118 FORMAT(/1X,'LOG-LIKE INDEX =',1X,F5.3,3X,'F-DIST DOF=',I3,',',I3)
  115 FORMAT(/1X,'P-SQUARED ADJ FOR DOF=',1X,F5.3)
C
  142 FORMAT(/1X,'BURNS ET AL(76)TRR PSEUDO RSQ=',1X,F8.3)
C
C     COMPUTE STAT TO TEST +VE SEMI DEF
      STAT=0
      DO 89 K1=1,L
      DO 89 K2=1,L
      STAT=STAT-B(K1)*B(K2)*DERV2(K1,K2)
   89 CONTINUE
      WRITE(6,123) STAT
  123 FORMAT(/1X,'STAT FOR +VE DEF =',1X,F8.3,4X,'NEED >=0')
C
```

```
      STAT=B(2)/B(3)
      WRITE(6,143) STAT
  143 FORMAT(////,1X,'VOT SAVINGS= B(2)/B(3)=',F8.3)
C
C
C
C
    4 RETURN
      END
C
C
C
C
C
```

```
      SUBROUTINE SMAVAR(M,L,IA)
C
C      THIS ROUTINE SELECTS REQUIRED SAMPLE, ASSIGNS CHOSEN VARIABLES
C      AND DELETES CASES WITH MISSING VALUES
C
      INTEGER IV(15),IVA(100,15)
      REAL*8 X(60),EXPLAN(400,12),AVAR(400,12),SY(400),SUMY,PSUM
      COMMON/VCOM/EXPLAN,PSUM,SY,SUMY,X,IVA,IV,N
C
      ST=X(15)
      NCR=X(8)
C
C  CHECK IF CAR AVAIL SAMPLE
      IF(IV(3).EQ.1) GOTO 2
C   CHECK IF HEADS SAMPLE
      IF(IV(3).EQ.2) GOTO 3
      GOTO 4
C
    2 IF(NCR.EQ.13) GO TO 1
      IF(NCR.LT.1) GOTO 1
      GOTO4
C
    3 IF(ST.GT.1.5) GOTO 1
C
    4 CONTINUE
C
C
C   ASSIGN EXPLAN VARS
C      .
      AVAR(M,1)=1.0
      LL=L+1
      DO 5 K=1,L
    5 AVAR(M,K+1)=X(IVA(IA,K))
C
      IF(LL.LT.6) GO TO 8
C
      IF(X(20).EQ.13) GO TO 1
      DO 6 K=6,LL
      IF(AVAR(M,K).EQ.13) GOTO 1
    6 CONTINUE
C
    8 N=N+1
      SY(N)=0
      IF(X(20).EQ.5) SY(N)=1.0
      IF(X(20).EQ.6) SY(N)=1.0
      SUMY=SUMY+SY(N)
C
      EXPLAN(N,1)=AVAR(M,1)
      EXPLAN(N,2)=AVAR(M,2)-AVAR(M,3)
      EXPLAN(N,3)=AVAR(M,4)-AVAR(M,5)
      LP=LL-2
C
      IF(LP.LT.4) GO TO 1
C
      DO 7 K=4,LP
      KK=K+2
    7 EXPLAN(N,K)=AVAR(M,KK)
C
C
C
```

```
      1 RETURN
        END
C
C
C
C
C
C
C
```

```
      SUBROUTINE SMVCOV(EXPLAN,L,N,B,VARCOV,AVX,AVXB,VARXB)
C
C     THIS ROUTINE COMPUTES VARIANCE COVARIANCE MATRIX OF THE
C      CHOSEN EXPLANATORY VARIABLES
C       IT ALSO COMPUTES CORRELATION COEFFICIENTS, AVX, AVXB, VARXB
C
      REAL*8 AVX(12),TOTX(12),SSQ(12),SXS(12,12),VARI(12),
     * VARCOV(12,12),X(60),EXPLAN(400,12),SY(400),CCF(12,12),SUMY,
     * B(12),AVXB,VARXB
      INTEGER IV(15),IVA(100,15)
C      COMMON/VCOM/EXPLAN,PSUM,SY,SUMY,X,IVA,IV,N
C
C
      DO 12 K1=1,L
      DO 12 K2=1,L
      AVX(K1)=0.0
      TOTX(K1)=0.0
      SSQ(K1)=0.0
   12 SXS(K1,K2)=0.0
      DO 13 I=1,N
      DO 13 K=1,L
      TOTX(K)=TOTX(K)+EXPLAN(I,K)
   13 SSQ(K)=SSQ(K)+(EXPLAN(I,K)**2)
      DO 18 K=1,L
      DO 18 K1=1,L
      DO 18 I=1,N
      SXS(K,K1)=SXS(K,K1)+EXPLAN(I,K)*EXPLAN(I,K1)
   18 CONTINUE
      DO 14 K=1,L
   14 AVX(K)=TOTX(K)/N
      DO 15 K1=1,L
      DO 15 K2=1,L
      VARI(K1)=(SSQ(K1)/N)-(AVX(K1)**2)
      VARCOV(K1,K2)=(SXS(K1,K2)/N)-(AVX(K1)*AVX(K2))
   15 CONTINUE
      LX=2
      DO 25 K1=LX,L
      DO 25 K2=LX,L
   25 CCF(K1,K2)=VARCOV(K1,K2)/(DSQRT(VARI(K1))*DSQRT(VARI(K2)))
C
      WRITE(6,200)
      DO 16 K=1,L
   16 WRITE(6,201) AVX(K),VARI(K)
      WRITE(6,202)
      DO 17 K2=1,L
   17 WRITE(6,203) (VARCOV(K1,K2),K1=1,L)
      WRITE(6,204)
      DO 26 K2=LX,L
   26 WRITE(6,203)(CCF(K1,K2),K1=LX,L)
  200 FORMAT(//////1X,'AVERAGE VALUES AND VARIANCES OF VARIABLES')
  201 FORMAT(/4X,F12.5,2X,F12.5)
  202 FORMAT(/1X,'VARIANCE-COVARIANCES OF EXPLAN VARS')
  203 FORMAT(/2X,12F9.3)
  204 FORMAT(/1X,'CORRELATION COEFFICIENTS')
C
      VARXB=0
      AVXB=0
      DO 2 K1=1,L
      AVXB=AVXB+B(K1)*AVX(K1)
```

```
      DO 2 K2=1,L
    2 VARXB=VARXB+B(K1)*B(K2)*VARCOV(K1,K2)
      WRITE(6,205) AVXB,VARXB
  205 FORMAT(/1X,'AVXB=',1X,F8.3,4X,'VARXB=',F8.3)
C
      RETURN
      END
C
C
C
CC
C
```

```
      SUBROUTINE SMEL(EXPLAN,B,ELPROB,SUMY,L,N)
C
C     THIS ROUTINE COMPUTES VARIOUS ELASTICITY MEASURES
C     AGGREGATE,MICRO AND APPROX ARC (WITHOUT RE-ESTIMATION)
C
      REAL*8 ELV(400),EXPLAN(400,12),B(12),ELVX(400),ELPROB(400),
     * ELPR(400),EPR(400),SUMEL(12),SUMEL1(12),AVX(12),DERV2(12,12),
     * PPSUM,PSUM,AVP,DIFF,AVVP,ELAST,ELAST1,PBAR,ELAST2,TOTX(12),
     * EL(400),XB(400),WEL1,WEL,CWEL,SUMY,SUMYN,ELL(400,12),TL,AL,VL,SL,
     * AET(12),AEB(12),AE(12),INC,PPSUMX(12),TOP(12),BOT(12),AEL(12),
     * CR,CR1,CHX(12)
      COMMON/GR/IGRN
C
C
C     COMPUTE ELASTICITIES & AV PROB
C     INITIALISE
      ELAST=0.0
      ELAST1=0.0
      PSUM=0.0
      PPSUM=0.0
      AVP=0.0
      AVVP=0.0
      DO 80 I=1,N
      ELV(I)=0.0
      ELVX(I)=0.0
      ELPROB(I)=0.0
      EPR(I)=0.0
C
      CWEL=0.0
      WEL=0.0
      DIFF=0.0
   80 CONTINUE
      DO 82 K=1,L
      PPSUMX(K)=0.0
      TOTX(K)=0.0
      SUMEL(K)=0.0
      SUMEL1(K)=0.0
   82 CONTINUE
      NPP1=0
      NPP2=0
      SSP=0
      SSP1=0
C
      WRITE(6,100)
  100 FORMAT('1',1X,'****ELASTICITY MEASURES',//)
C
      SUMYN=SUMY/N
C
      DO 83 I=1,N
      DO 84 K=1,L
      ELV(I)=ELV(I)+EXPLAN(I,K)*B(K)
      TOTX(K)=TOTX(K)+EXPLAN(I,K)
   84 CONTINUE
      ELVX(I)=DEXP(ELV(I))
      ELPROB(I)=ELVX(I)/(1+ELVX(I))
      EPR(I)=1-ELPROB(I)
      PSUM=PSUM+ELPROB(I)
      PPSUM=PPSUM+ELPROB(I)*EPR(I)
      SP=0
      SP1=0
```

```
      IF(ELPROB(I).LT.0.5) NPP1=NPP1+1
      IF(ELPROB(I).LT.0.5)SP=EPR(I)
      SSP=SSP+SP
      IF(ELPROB(I).GE.0.5) NPP2=NPP2+1
      IF(ELPROB(I).GE.0.5)SP1=ELPROB(I)
      SSP1=SSP1+SP1
C
      DO 85 K=1,L
      PPSUMX(K)=PPSUMX(K)+ELPROB(I)*EPR(I)*EXPLAN(I,K)
      ELL(I,K)=EPR(I)*B(K)*EXPLAN(I,K)
      SUMEL(K)=SUMEL(K)+ELPROB(I)*EPR(I)*B(K)*EXPLAN(I,K)
   85 CONTINUE
C      WRITE(6,151) ELPROB(I),Y(I)
C
   83 CONTINUE
  151 FORMAT(/,1X,'INDIV ELPROBS=',1X,F8.3,4X,'CHOSEN MODE =',1X,F4.2)
C
      AVXB=0
      DO 72 K=1,L
       AVX(K)=TOTX(K)/N
   72 AVXB=AVXB+AVX(K)*B(K)
      DO 71 I=1,N
      CWEL=CWEL+ELPROB(I)*EPR(I)*AVXB
      WEL=WEL+ELPROB(I)*EPR(I)*(DLOG(ELPROB(I)/EPR(I))-AVXB)
   71 CONTINUE
C
      WRITE(6,139) NPP1,NPP2
  139 FORMAT(/1X,'NO. OBS P.LT.0.5=',1X,I3,4X,'P.GE.0.5=',1X,I3)
C      .
      WRITE(6,102) AVXB
  102 FORMAT(/1X,'DISTRIBN OF LINEAR COMB OF EXPLAN VARS'
     *,//,1X,'  AVXB=',F8.3)
C
      IGRN=IGRN+1
      CALL SMDIST(ELV,L,N)
C      -
      WEL1=WEL/PSUM
      WEL1=(-1)*WEL1
      CWEL=CWEL/PSUM
      AVP=PSUM/N
      DIFF=SUMYN-AVP
      AVVP=PPSUM/N
      DO 86 K=1,L
      AVX(K)=TOTX(K)/N
      ELAST=SUMEL(K)/PSUM
      ELAST1=B(K)*AVX(K)*(AVVP/AVP)
      ELAST2=(1-AVP)*B(K)*(AVX(K))
      WRITE(6,120) ELAST,ELAST1,ELAST2
   86 CONTINUE
  120 FORMAT(/1X,'AGG ELAST=',F10.3,4X,'NAIVE=',F10.3,4X,
     * 'REPRES IND=',F10.3)
C
      WRITE(6,140)WEL1,CWEL
  140 FORMAT(//1X,'DISCRETE WESTIN VARIANCE ELAST=',F10.3,4X,
     * 'CORRECTED=',F10.3)
C
C      WRITE(6,138) AVX
      LL=L
      IF(L.GT.3) LL=4
```

```
C
      DO 70 K=2,LL
      IGRN=IGRN+1
      TL=0
      SL=0
      DO 74 I=1,N
      TL=TL+ELL(I,K)
      SL=SL+(ELL(I,K)**2)
   74 EL(I)=ELL(I,K)
      AL=TL/N
      VL=(SL/N)-(AL**2)
      WRITE(6,101)K,AL,VL
C      CALL SMDIST(EL,L,N)
   70 CONTINUE
  101 FORMAT(/1X,'DISTRIBN OF INDIV ELASTS VARIABLE ',I2
     * ,4X,'MEAN=',F10.3,4X,'VARIANCE=',F10.3)
C
  121 FORMAT(//1X,'PROP OF CAR USERS=',F10.3,//,1X,
     * 'AV PROB=',F10.3,//,1X,'DIFFERENCE=',F10.3)
  119 FORMAT(//1X,'SUM OF PROBS =',1X,F12.5,4X,'SUM Y(I)S=',1X,F12.5)
  138 FORMAT(//1X,'AV VALUES OF DEP VARS =',/(1X,F8.3))
C
C   COMPUTE ARC ELASTS USING APPROX FORMULA
C
      WRITE(6,141)
  141 FORMAT(//,1X,'ARC ELASTS LIN APPROX FOR',1X,
     * 'ABSOLUTE CHANGE TDIFF & CDIFF OF -10,-5,5,10')
      INC=-15
      DO 10 K2=1,5
      INC=INC+5
C      IF(INC.EQ.0) GOTO 10
      DO 11 K1=2,3
      AET(K1)=B(K1)*PPSUM*(2*AVX(K1)+INC)
      AEB(K1)=2*PSUM+B(K1)*PPSUM*INC
   11 AE(K1)=AET(K1)/AEB(K1)
      WRITE(6,142) INC,(AE(K),K=2,3)
   10 CONTINUE
  142 FORMAT(/,1X,'CHANGE OF ',F6.2,6X,'AE=',12F8.3)
C
      WRITE(6,143)
  143 FORMAT(//,1X,'ARC ELASTS APPROX %CHANGE ALL L VARS',1X,
     * '-10,-5,5,10%')
      INC=-0.15
      DO 12 K2=1,5
      INC=INC+0.05
C      IF(INC.EQ.0.0) GOTO 12
      DO 13 K1=1,L
      CHX(K1)=DABS(AVX(K1))*INC
      IF(CHX(K1).EQ.0) GO TO 12
      TOP(K1)=B(K1)*(PPSUMX(K1))*(2*AVX(K1)+CHX(K1))
      BOT(K1)=2*AVP*TOTX(K1)+B(K1)*DABS(PPSUMX(K1))*CHX(K1)
   13 AEL(K1)=TOP(K1)/BOT(K1)
      WRITE(6,142) INC,(AEL(K),K=1,L)
   12 CONTINUE
C
C
      WRITE(6,119) PSUM,SUMY
      WRITE(6,121) SUMYN,AVP,DIFF
C
```

```
C
C
      RETURN
      END
C
C
C
C
C
      SUBROUTINE SMCMC(ELPROB,Y,L,N)
C
C     THIS ROUTINE COMPUTES THE GOODNESS OF FIT MEASURES BASED
C     UPON THE COST OF MISSCLASSIFICATIONS OF OUTCOMES
C     DEVELOPED IN DOMENCICH AND MCFADDEN
C
      REAL*8 AVP,ELPROB(400),Y(400),
     * C1,C2,DEL(400),EC1,EC2,CC1,CC2,CC3,PCC,CMI1,CMI2,PSUM
C     COST OF MISSCLASSIF STATS
      DEL1=0.0
      EC1=0.0
      EC2=0.0
      CC1=0.0
      CC2=0.0
      CC3=0.0
      PSUM=0
C
      WRITE(6,100)
  100 FORMAT(////,1X,'****COST OF MISCLASSIFICATION STATISTICS',//)
C
      DO 1 I=1,N
    1 PSUM=PSUM+ELPROB(I)
      AVP=PSUM/N
C
      C1=1/AVP
      C2=1/(1-AVP)
      DO 77 I=1,N
      DEL(I)=0.0
      IF(ELPROB(I).GE.0.5) DEL(I)=1.0
      DEL1=DEL1+(Y(I)*DEL(I))+((1-Y(I))*(1-DEL(I)))
      EC1=EC1+ELPROB(I)*(1-DEL(I))+(1-ELPROB(I))*DEL(I)
      EC2=EC2+ELPROB(I)*(1-DEL(I))*C1+(1-ELPROB(I))*DEL(I)*C2
      CC1=CC1+Y(I)*(1-DEL(I))+(1-Y(I))*DEL(I)
      CC2=CC2+Y(I)*(1-DEL(I))*C1+(1-Y(I))*DEL(I)*C2
      CC3=CC3+Y(I)*0.5*C1+(1-Y(I))*0.5*C2
   77 CONTINUE
      PCC=DEL1/N
      CMI1=1-(CC1/N)
      CMI2=1-(CC2/CC3)
C
      WRITE(6,122) EC1,EC2,CMI2,CMI1
      WRITE(6,143) DEL1,PCC
  143 FORMAT(/1X,'NO CORRECTLY CLASSIFIED=',1X,F8.3,4X,
     *'PROPORTION=',1X,F8.3)
  122 FORMAT(/1X,'EXPECTED COST OF MISSCLASS E(C):C=1=',1X,F12.5,4X,
     *'ASSUME C=1/AV PROB=',1X,F12.5,4X,//,18X,'STATS-ASSUME C=1/P:',1X,
     *F12.5,14X,'ASSUME C=1:',F12.5)
C
      RETURN
      END
```

```
C
C
C
C
CC
C
C
C
      SUBROUTINE SMTALV(B,VARCOV,ELPROB,AVX,L,N)
C
C     THIS ROUTINE COMPUTES E(P) USING THE TAYLOR EXPANSION
C     APPROACH OF TALVITIE
C
      REAL*8 B(12),VARCOV(12,12),AVX(12),
     * VARXB,VARXB1,AVXB,SDXB,SDBX,PBAR,PBARS,TEP1,TEP,APB,ATEP,ATEP1,
     * AVP,ELPROB(400),PSUM,PBAR1,ADJ
C
C
C
      PSUM=0
      DO 1 I=1,N
    1 PSUM=PSUM+ELPROB(I)
      AVP=PSUM/N
C
C     COMPUTE E(P) TALVITIE
C
      AVXB=0.0
      VARXB=0.0
      VARXB1=0.0
      DO 87 K1=1,L
      AVXB=AVXB+B(K1)*AVX(K1)
      DO 88 K2=1,L
      VARXB1=VARXB1+B(K1)*B(K1)*VARCOV(K1,K1)
   88 VARXB=VARXB+B(K1)*B(K2)*VARCOV(K1,K2)
   87 CONTINUE
      SDBX=DSQRT(VARXB1)
      SDXB=DSQRT(VARXB)
      PBAR=(DEXP(AVXB))/(1+DEXP(AVXB))
      PBARS=PBAR*(PBAR-1)*(PBAR-0.5)
      TEP1=PBAR+VARXB1*PBARS
      TEP=PBAR+VARXB*PBARS
C
C  USING AV PROB
      APB=AVP*(AVP-1)*(AVP-0.5)
      ATEP1=AVP+VARXB1*APB
      ATEP=AVP+VARXB*APB
C
      WRITE(6,124) TEP,ATEP,TEP1,ATEP1
      WRITE(6,125) PBAR,AVXB,VARXB,VARXB1
  124 FORMAT(/1X,'USING NAIVE          TALVITIE E(P)=',1X,F8.3,4X,
     * //,1X,'USING AVPROB TALV E(P)=',1X,F8.3
     * ,//,4X,'USING COVAR(K,K)=',1X,F8.3,1X,F8.3)
  125 FORMAT(////1X,'  NAIVE E(P)=DEXP(AVXB)/(1+DEXP(AVXB)=',
     *1X,F8.3,4X,//,1X,
     *'AVERAGE XB=',1X,F8.3,4X,'VAR XB=',1X,F8.3,4X,//,1X,
     *'USING COVAR(K,K) VAR XB=',1X,F8.3,'1')
C
      ADJ=((DSQRT(VARXB)-0.5)/AVXB)*((PBAR-0.5)**2)
      PBAR1=PBAR+ADJ
```

```
      WRITE(6,126) PBAR1
  126 FORMAT(///,1X,'ADJUSTMENT=',F8.3,4X,'NAIVE WITH TALVITIE',1X,
     * 'ADJUSTMENT=',F8.3)
      RETURN
      END
C
C
C
C
C
C
C
```

```
      SUBROUTINE SSBD(AVXB,VARXB,AVX,ELPROB,AP,ASB,B,L,N,ILL)
C
C     THIS ROUTINE COMPUTES SB DISTRIBUTION FOR GIVEN PARAMETERS
C     (AVXB,VARXB) AND THE RFD FOR THE ESTIMATED PROBABILITIES
C     (ELPROB)      IF ILL NE 0 THESE ARE ILLUSTRATED
C     NUMERICAL INTEGRATION IS USED (NAGROUTINE) TO COMPUTE
C     E(P), ELASTS, AND GOF STATS FOR THE SB DISTRIBUTION
C
C
      INTEGER*4 NP(2),CODE(2)/42,43/
      REAL*4 YARF1(2,41),XX(2,41),YARF(2,41),XX1(2,41)
      REAL*8 B(12),AVX(12),PY1(41),PY2(41),PY3(41),
     * PY4(41),PY5(41),PY6(41),PY7(41),ELM,ELAV,REL,DIFFE,PC,APC,CI1,CI2,
     * PC1,PC2,ELAV1,PCA,APCA,CIA1,CIA2,PP,PP1,TT,MOR,
     * VARXB,AVXB,SBC1,SBA,ASB(41),AP(41),SSB,SBC2,SBCA,SBC,SB,
     * ARF(41),P,ELPROB(400),IPY1,IPY2,IPY3,IPY4,IPY5,IPY6,IPY7,
     * ER1,ER2,ER3,ER4,ER5,ER6,ER7,ELVAR,SEP,ARF1(41)
      COMMON/GR/ IGRN
C
      WRITE(6,100)
  100 FORMAT(//////,1X,'***** SB DISTRIBUTION ',/)
C
C     COMPUTE SB DISTRIBNS ETC
      SBC1=1/(2*VARXB)
      SBA=1/DSQRT(6.2831853*VARXB)
      ASB(1)=0
      ASB(41)=0.0
      AP(1)=0
      AP(41)=1
      P=0
      DO 90 J=2,40
      P=P+0.025
      P1=P-0.025
      SBB=1/(P*(1-P))
      SBC2=(DLOG(P/(1-P))-AVXB)**2
      SBCA=-SBC1*SBC2
      SBC=DEXP(SBCA)
      SB=SBA*SBB*SBC
      ASB(J)=SB
      AP(J)=P
   90 CONTINUE
C
      DO 74 K=1,41
   74 ARF(K)=0.0
      DO 91 J=1,40
      DO 91 I=1,N
      IF(ELPROB(I).GE.AP(J).AND.ELPROB(I).LT.AP(J+1))ARF(J)=ARF(J)+1
   91 CONTINUE
C      DO 76 J=1,41
C      WRITE(6,126) AP(J),ASB(J),ARF(J)
C   76 CONTINUE
  126 FORMAT(/1X,'PROB=',1X,F8.3,4X,'SB VALUES=',1X,F8.3,4X,
     *'OBSERVED=',1X,F8.3)
C
      SARF=0
      SSB=0
      DO 93 K=1,41
      SARF=SARF+ARF(K)
      SSB=SSB+ASB(K)
   93 CONTINUE
```

```
C
      IF(ILL.EQ.0) GOTO 141
C
C
C
C
C   ILLUSTRATE FREQS & SB DISTRIBN
C
      DO 94 K1=1,41
      YARF(1,K1)=ARF(K1)*(SSB/SARF)
      YARF(2,K1)=ASB(K1)
      ARF1(K1)=ARF(K1)*(SSB/SARF)
      DO 94 K2=1,2
      XX(K2,K1)=AP(K1)
   94 CONTINUE
C
      IGRN=IGRN+1
      WRITE(6,140)
  140 FORMAT(/,1X,'*REL FREQ     + SB DISTRIBN')
C
C      NPMAX=41
C      LINES=NPMAX
C      NDIM=2
C      MM=2
C      NP(1)=41
C      NP(2)=41
C      CALL IMPGRAPH9(XX,YARF,NP,CODE,MM,LINES,NPMAX,IGRN)
C
C      CALL SBILL(YARF,ASB,AP)
C
      CALL SBILL(ARF1,ASB,AP)
C
C      DO 2 I=1,41
C    2 WRITE(5,100) YARF(1,I),YARF(2,I)
C  100 FORMAT(2F8.3)
C
C
  141 CONTINUE
C
C   NUMERICAL INTEGRATION
C
      DO 95 K=1,41
      PY1(K)=AP(K)*ASB(K)
      PY7(K)=ASB(K)
   95 CONTINUE
C
      AP(1)=0.0000001
      AP(41)=0.99999999
      DO 195 K=1,41
      PY2(K)=(1-AP(K))*ASB(K)
      PY3(K)=AP(K)*(1-AP(K))*ASB(K)
      PY4(K)=AP(K)*(1-AP(K))*(DLOG(AP(K)/(1-AP(K)))-AVXB)
     * *ASB(K)
      PY7(K)=ASB(K)
  195 CONTINUE
      DO 96 K=1,21
   96 PY5(K)=(1-AP(K))*ASB(K)
      MM=0
      DO 97 K=21,41
```

```
      MM=MM+1
   97 PY6(MM)=AP(K)*ASB(K)
      IFAIL=0
      CALL D01GAF(AP,PY7,41,IPY7,ER7,IFAIL)
      WRITE(6,101) IPY7,ER7
      CALL D01GAF(AP,PY1,41,IPY1,ER1,IFAIL)
      WRITE(6,127) IPY1,ER1
C
      IF(ILL.EQ.0) GOTO 4
C
      CALL D01GAF(AP,PY2,41,IPY2,ER2,IFAIL)
      WRITE(6,128) IPY2,ER2
      CALL D01GAF(AP,PY3,41,IPY3,ER3,IFAIL)
      WRITE(6,129) IPY3,ER3
      CALL D01GAF(AP,PY4,41,IPY4,ER4,IFAIL)
      WRITE(6,130) IPY4,ER4
      CALL D01GAF(AP,PY5,21,IPY5,ER5,IFAIL)
      WRITE(6,131) IPY5,ER5
      CALL D01GAF(AP,PY6,20,IPY6,ER6,IFAIL)
      WRITE(6,132) IPY6,ER6
  101 FORMAT(//1X,'INTEG OF SB DISTRIBN=',F8.3,4X,'ERROR=',F8.3)
  127 FORMAT(////1X,'WESTIN NI E(P)=',1X,F8.3,4X,'INTEG ERROR=',1X,F8.3)
  128 FORMAT(////1X,'INT (1-P)F(P)=',1X,F8.3,4X,'ERROR=',1X,F8.3)
  129 FORMAT(/1X,'INT P(1-P)F(P)=',1X,F8.3,4X,'ERROR=',1X,F8.3)
  130 FORMAT(/1X,'P(1-P)*LOG(P/1-P)-AV*F(P)=',F8.3,4X,'ERROR=',1X,F8.3)
  131 FORMAT(/1X,'(1-P)F(P) I=1,M=',1X,F8.3,4X,'ERROR=',1X,F8.3)
  132 FORMAT(/1X,'PF(P) I=M,N=',1X,F8.3,4X,'ERROR=',1X,F8.3,////)
C
      ELVAR=(-1)*(IPY2*AVXB)/IPY1
      ELAV=IPY4/IPY1
      DIFFE=(IPY1*(1-IPY1))/IPY3
C
      DO 98 K=1,L
      ELM=(B(K)*DABS(AVX(K))*IPY3)/IPY1
      REL=((B(K)*DABS(AVX(K))*IPY1)*(1-IPY1))/IPY1
      WRITE(6,133) ELM,REL
   98 CONTINUE
      WRITE(6,134) DIFFE,ELAV,ELVAR
C
  133 FORMAT(/1X,'ELAST OF MEAN=',1X,F8.3,4X,
     *'ELAST OF MEAN: REPRES IND=',1X,F8.3)
  134 FORMAT(////,1X,'DIFF BET ELASTS OF MEAN=',1X,F8.3,
     * //,1X,'ELAST OF VAR OF XB=',1X,F8.3,4X,'CORRECTED=',F8.3)
      PC=IPY5+IPY6
      APC=(PC*(1-PC))/N
      CI1=PC+(1.96*DSQRT(APC))
      CI2=PC-(1.96*DSQRT(APC))
      PC1=0
      PC2=0
C
      DO 1 I=1,N
      PP1=1-ELPROB(I)
      PP=ELPROB(I)
      IF(ELPROB(I).LT.0.5) PC1=PC1+PP1
      IF(ELPROB(I).GE.0.5) PC2=PC2+PP
    1 CONTINUE
C
C
      PCA=(PC1+PC2)/N
```

```
061         APCA=PCA*(1-PCA)/N
062         CIA1=PCA+(1.96*DSQRT(APCA))
063         CIA2=PCA-(1.96*DSQRT(APCA))
064         WRITE(6,136) PC,CI1,CI2
065         WRITE(6,137) PCA,CIA1,CIA2
066   C
067      136 FORMAT(////1X,'NUM INT P(C)=',1X,F8.3,4X,'CONFID INT=',
068        *1X,F8.3,4X,F8.3)
069      137 FORMAT(/1X,'DISCRETE P(C)=',1X,F8.3,4X,'CIS=',1X,F8.3,4X,F8.3)
070   C
071       4  CONTINUE
072   C
073         SEP=IPY1+((1-IPY7)/IPY7)*IPY1
074         WRITE(6,138) SEP
075      138 FORMAT(//,1X,'WESTIN E(P) SCALED FOR INTSB.NE.0=',F8.3)
076   C
077   C
078   C
079         RETURN
080         END
081   C
082   C
```

```
      SUBROUTINE SIMSB(ELPROB,AVX,AVXB,B,VARXB,ASB,ASB1,AP,L,N,IV,INC,
     * IA,ILL)
C
C    THIS ROUTINE ILLUSTRATES THE EFFECTS OF CHANGING
C    MEANS OF THE SB DISTRIBUTION
C     IA=0 PERCENT IA=1 ABSOLUTE CHANGE
C    IF ILL=0 GRAPH OF BEFORE AND AFTER SUPRESSED
C
      REAL*8 AVX(12),AVXB,VARXB,B(12),ASB(41),ASB1(41),AP(41),INC,
     * AVXB1,ELPROB(400),AINC
C
      WRITE(6,100)
  100 FORMAT('1',//,1X,'EFFECT OF CHANGING SB PARAMS -APPROX CHANGE',1X,
     * 'MEAN')
C
      IF(IA.EQ.1) GOTO1
C
      AINC=INC/100
      AVXB1=AVXB+(B(IV)*AINC*DABS(AVX(IV)))
      GO TO 2
C
    1 AVXB1=AVXB+INC*B(IV)
C
    2 WRITE(6,101) IV,INC,IA
  101 FORMAT(/1X,'EFFECT OF CHANGING MEAN OF VAR=',1X,I2,4X,'BY',
     * 1X,F8.3,2X,'  IA= ',I2,//,1X,'IF IA=0 PERCENT IA=1 ABSOLUTE')
C
      CALL SSBD(AVXB1,VARXB,AVX,ELPROB,AP,ASB1,B,L,N,0)
      IF(ILL.EQ.0) GOTO 4
      WRITE(6,102)
  102 FORMAT(/,1X,'*** SB SIMULATION  *ORIGINAL  +RESULTING')
C      CALL SBILL(ASB,ASB1,AP)
C
    4 RETURN
      END
C
C
C
C
```

```
      SUBROUTINE RESIM(EXPLAN,B,ELPROB,ASB,ASB1,L,N,IV,INC,IA,ILL)
C
C    THIS ROUTINE ILLUSTRATES THE EFFECT OF A PERCENTAGE CHANGE
C    (IA=0) OR AN ABSOLUTE CHANGE (IA=1) IN SPECIFIED VARIABLE (IV)
C    ON THE ESTIMATED SB DISTN BY RESTIMATING VARCOV STRUCTURE
C     IF ILL=0 GRAPH OF BEFORE AND AFTER SUPRESSED
C
      REAL*8 INC,EXPLAN(400,12),B(12),ELPROB(400,12),XX(400,12)
     * ,VARC(12,12),AVX1(12),ASB(41),ASB1(41),AVXB1,VARXB1,AP(41),AINC
C
      WRITE(6,100) IV,INC,IA
  100 FORMAT('1',//,1X,'THE EFFECT OF A CHANGE IN EXPLAN VAR NO.',1X,I2,
     * 4X,'OF ',F8.3,//
     *,1X,'    IA=',1X,I2,2X,'IF IA=1 ABSOLUTE CHANGE IF IA=0 % CHANGE')
C
      DO 1 I=1,N
      DO 1 K=1,L
    1 XX(I,K)=EXPLAN(I,K)
C
      IF(IA.EQ.1) GOTO 2
C
      DO 3 I=1,N
      AINC=INC/100
    3 XX(I,IV)=XX(I,IV)+(AINC*DABS(XX(I,IV)))
      GOTO 4
C
    2 DO 5 I=1,N
    5 XX(I,IV)=XX(I,IV)+INC
C
    4 CONTINUE
C
      CALL SMVCOV(XX,L,N,B,VARC,AVX1,AVXB1,VARXB1)
      IL=0
      CALL SSBD(AVXB1,VARXB1,AVX1,ELPROB,AP,ASB1,B,L,N,IL)
      IF(ILL.EQ.0) GO TO 6
      CALL SBILL(ASB,ASB1,AP)
C
    6 RETURN
      END
C
C
C
C
```

```
      SUBROUTINE SBILL(ASB,ASB1,AP)
C
C    THIS ROUTINE ILLUSTRATES EFFECTS OF CHANGES IN SB PARAMETERS
C
      INTEGER*4 NP(2),CODE(2)
      REAL*4 XX(2,41),YY(2,41)
      REAL*8 AVX(12),AVXB,B(12),VARXB,ASB(41),ASB1(41),ELPROB(400),
     * AVXB1,AP(41)
      DATA CODE/42,43/
      COMMON/GR/IGRN
C
      DO 1 K=1,41
      YY(1,K)=ASB(K)
      YY(2,K)=ASB1(K)
      DO 1 K1=1,2
      XX(K1,K)=AP(K)
    1 NP(K1)=41
C
      IGRN=IGRN+1
C
      NPMAX=41
      LINES=NPMAX
      NDIM=2
      MM=2
      WRITE(6,100)IGRN
  100 FORMAT(/,1X,'   * SEE GRAPH NO.',1X,I3)
C
C     CALL IMPGRAPH9(XX,YY,NP,CODE,MM,LINES,NPMAX,IGRN)
C
      RETURN
      END
C
C
C
C
C
```

```
      SUBROUTINE PINC(ELPROB,EXPLAN,B,AVX,N,L,IV,IC,IA)
C
C    THIS ROUTINE RE-ESTIMATES PROBS AFTER A CHANGE IN EXPLAN
C    VAR(IV) OF MAGN INC USING INCREMENTAL LOGIT
C      IF IA=0 %CHANGE    IF IA=1 ABSOLUTE CHANGE
C    ALSO COMPUTES ARC ELASTS FOR RELEVANT VARIABLE
C
      REAL*8 INC,ELPROB(400),EXPLAN(400,12),B(12),CHXB(400),
     * ECH(400),CAE(400),PROB(400),TOTP,AVPR,AVX(12),
     * EL,TOP,BOT,PDIF,XDIF,AINC,IC
      COMMON/GR/IGRN
C
      INC=IC
      MM=0
      DO 6 J=1,2
      IF(J.EQ.2) INC=INC/2
C
      AVP=0
      TOTP=0
      DO 1 I=1,N
      IF(IA.EQ.1) GOTO 2
      AINC=INC/100
      CHXB(I)=AINC*B(IV)*DABS(EXPLAN(I,IV))
      GO TO 3
    2 CHXB(I)=B(IV)*INC
    3 ECH(I)=DEXP(CHXB(I))
      CAE(I)=(1-ELPROB(I))/ELPROB(I)
      PROB(I)=ECH(I)/(CAE(I)+ECH(I))
      AVP=AVP+(ELPROB(I)/N)
    1 TOTP=TOTP+PROB(I)
C
      AVPR=TOTP/N
C
      IF(J.EQ.2) GOTO 6
C
      WRITE(6,100)IV,INC,IA,AVPR
  100 FORMAT('1',//,1X,'*****INCREMENTAL LOGIT',//,1X,'RESULT FOR CHANGE
     * IN VAR ',1X,I2,2X,'OF',1X,F8.3,//,1X,'IA=',I2,4X,
     * 'IF IA=0 PERCENT CHANGE      IA=1 ABSOLUTE CHANGE',//,1X,
     * 'NEW AVERAGE PROBABILITY =',F8.3)
C
C
      EL=(1-AVPR)*B(IV)*AVX(IV)
      WRITE(6,101) EL
  101 FORMAT(//,1X,'REPRES INDIV ARC ELAST=',F8.3)
C
      IF(IA.EQ.1) GOTO 4
C
      AINC=INC/100
      PDIF=AVPR-AVP
      XDIF=DABS(AVX(IV))*AINC
      TOP=PDIF*(2*AVX(IV)+XDIF)
      BOT=XDIF*(2*AVP+PDIF)
      EL=TOP/BOT
      MM=MM+1
      WRITE(6,102) MM,EL
  102 FORMAT(//,1X'ARC ELAST NO. ',1X,I2,1X,'=',F8.3)
C
      EL=(PDIF/XDIF)*(AVX(IV)/AVP)
```

```
      MM=MM+1
      WRITE(6,102) MM,EL
      EL=(PDIF/XDIF)*((AVX(IV)+(XDIF/2))/AVPR)
      MM=MM+1
      WRITE(6,102) MM,EL
C
      EL=(PDIF/XDIF)*(AVX(IV)+(XDIF/2))
C
      GO TO 6
    4 CONTINUE
C
      PDIF=AVPR-AVP
      TOP=PDIF*(2*AVX(IV)+INC)
      BOT=INC*(2*AVP+PDIF)
      EL=TOP/BOT
      MM=MM+1
      WRITE(6,102)MM,EL
C
      EL=(PDIF/INC)*(AVX(IV)/AVP)
      MM=MM+1
      WRITE(6,102) MM,EL
      EL=(PDIF/INC)*((AVX(IV)+(INC/2))/AVPR)
      MM=MM+1
      WRITE(6,102)MM,EL
C
      EL=(PDIF/INC)*(AVX(IV)+(INC/2))
C
    6 CONTINUE
C
      EL=EL/AVPR
      MM=MM+1
      WRITE(6,102) MM,EL
C
C
      IGRN=IGRN+1
      WRITE(6,104)
  104 FORMAT(//1X,'DISTRIBUTION OF NEW PROBABILITIES')
      CALL SMDIST(PROB,L,N)
C
      RETURN
      END
C
C
C
C
C
C
```

```
      SUBROUTINE SMDIST(VAR,L,N)
C
C    THIS ROUTINE USES IMPGRAPH9 TO PLOT RFD OF INPUT
C    VARIABLE "VAR"
C
      REAL*8 VAR(400)
      REAL*4 VX(1,41),NX(1,41),NC,NB
      INTEGER NP(1),CODE(1)
      DATA CODE/42/
      COMMON/GR/IGRN
C
      DO 5 I=1,N
      IF(VAR(I).LT.0.0) GOTO 7
    5 CONTINUE
C
      X=VAR(1)
      DO 1 I=1,N
      IF(VAR(I).GT.X) X=VAR(I)
    1 CONTINUE
      NC=X/40
      VX(1,1)=0
      GO TO 8
C
    7 X=DABS(VAR(1))
      DO 6 I=1,N
      IF(DABS(VAR(I)).GT.X) X=DABS(VAR(I))
    6 CONTINUE
C
      NC=X/20
      VX(1,1)=-X
C
    8 WRITE(6,101) X
  101 FORMAT(/1X,'MAX VALUE=',F10.3)
C
      NB=0
      DO 2 J=2,41
      NB=NB+NC
    2 VX(1,J)=VX(1,1)+NB
      DO 3 J=1,41
    3 NX(1,J)=0.0
      DO 4 I=1,N
      DO 4 J=1,40
      IF(VAR(I).GT.VX(1,J).AND.VAR(I).LT.VX(1,J+1)) NX(1,J)=
     *NX(1,J)+1
    4 CONTINUE
C
      DO 10 K=1,41
   10 NX(1,K)=NX(1,K)/N
C
      WRITE(6,102) IGRN
  102 FORMAT(/,1X,'SEE GRAPH NO. ',I3)
      NP(1)=41
      NPMAX=41
      LINES=NPMAX
      NDIM=1
      MM=1
C     CALL IMPGRAPH9(VX,NX,NP,CODE,NDIM,NPMAX,LINES,IGRN)
C
      RETURN
      END
```

```
C
C
      SUBROUTINE CLASS(EXPLAN,B,L,N)
C
C   THIS ROUTINE DIVIDES THE TOTAL SAMPLE ON
C   THE BASIS OF CAR OWNERSHIP AND ESTIMATES NAIVE
C   E(P) OF SUBSAMPLES
C
      REAL*8 EXPLAN(400,12),B(12),AVXB(12),AVXB1(12),TOTX(12),
     * TOTX1(12),LCV,LCV1,EXPLCV,EXPL1,PROB,PROB1,AP
      INTEGER IV(15)
C
      IF(L.LE.3) GO TO 10
C
C
      NN=0
      NN1=0
      DO 6 K=1,L
      TOTX(K)=0.0
    6 TOTX1(K)=0.0
C
      DO 1 I=1,N
      IF(EXPLAN(I,4).NE.0) GO TO 2
      NN=NN+1
      DO 3 K=1,L
    3 TOTX(K)=TOTX(K)+EXPLAN(I,K)
      GO TO 1
    2 NN1=NN1+1
      DO 4 K=1,L
    4 TOTX1(K)=TOTX1(K)+EXPLAN(I,K)
    1 CONTINUE
C
      LCV=0
      LCV1=0.0

      DO 5 K=1,L
      AVXB(K)=B(K)*(TOTX(K)/N)
      AVXB1(K)=B(K)*(TOTX1(K)/N)
      LCV=LCV+AVXB(K)
    5 LCV1=LCV1+AVXB1(K)
C
      EXPLCV=DEXP(LCV)
      EXPL1=DEXP(LCV1)
      PROB=EXPLCV/(1+EXPLCV)
      PROB1=EXPL1/(1+EXPL1)
C
      WRITE(6,100) PROB,NN,PROB1,NN1
  100 FORMAT(//,1X,'CLASSIFICATION BY CAR OWNERSHIP',//,
     * 1X,'NAIVE FOR NON CAR OWNERS=',F8.3,4X,'NO. OBS=',F8.3,
     * //,1X,'NAIVE FOR CAR OWNERS=',F8.3,4X,'NO. OBS=',
     * F8.3)
C
      AP=(PROB+PROB1)/2
      WRITE(6,101) AP
  101 FORMAT(//,1X,'AVERAGE=',F8.3)
C
      AP=(PROB*NN+PROB1*NN1)/(NN1+NN)
      WRITE(6,102) AP
  102 FORMAT(//,1X,'WEIGHTED AVERAGE=',F8.3)
```

```
C
C
   10 RETURN
      END
C
C
C
C
C
C
C
      SUBROUTINE SBSIL(ASB,AASB,AP,N)
C
C   THIS ROUTINE PLOTS SIMULATIONS ON SAME GRAPH
C    PLOTS UP TO 6 GRAPHS
C
      DIMENSION NP(6),NCODE(6),NCD(6),XX(6,41),YY(6,41),
     * AASB(6,41),AP(41),ASB(41)
      DOUBLE PRECISION AASB,ASB,AP
      DATA NCD/42,43,44,45,46,64/
      COMMON/GR/ IGRN
C
      DO 1 K=1,41
      YY(1,K)=ASB(K)
      XX(1,K)=AP(K)
      NN=N-1
      DO 2 I=2,NN
      II=I-1
      YY(I,K)=AASB(II,K)
    2 XX(I,K)=AP(K)
      DO 3 I=1,N
      NCODE(I)=NCD(I)
    3 NP(I)=41
    1 CONTINUE
C
      IGRN=IGRN+1
      NPMAX=41
      LINES=NPMAX
      NDIM=N
      MM=N
      WRITE(6,100)IGRN
  100 FORMAT(//,1X'SEE GRAPH NO.',F8.3)
C     CALL IMPGRAPH9(XX,YY,NP,NCODE,MM,LINES,NPMAX,IGRN)
C
      RETURN
      END
C
C
C
```

APPENDIX 12

MULTINOMIAL LOGIT COMPUTER PROGRAM

This appendix presents the purpose written multinomial logit computer program, in this case considering 3 alternatives. As with the binary logit, the program is written in FORTRAN IV and compatible with the Edinburgh Multi Access System. To run the compiled program the following channel definitions are required.

```
DEFINE (6, .LP)
DEFINE (2, file name or terminal)
DEFINE (1, data file name)
FORTE (MNL, MNL1)
RUN ( MNLI)
```

Input to channel 2 can be either contained in file or typed on console.

The specifications required are best shown by example:

```
Ø3Ø93191Ø
a b c d
```

a = number of modes I2

b = total number of variables (no.vars x no.modes) I2

c = total no.observations I3

d = sample required

- Ø = tot sample
- 1 = car available sample
- 2 = heads only
- 3 = no.car available
- 4 = non heads

In response to the prompt or on the next line of the file:

```
22230100282900012600000Ø
a b c d  e     f
```

where: a=identifier variable X(22)

Mode 1

b = " " X(23)

c Ø1 = variable taking value 1

d ØØ = variable value zero

e same as above for mode 2 bus

f " " " " " 3 walk

Thus, there are 2 generic variables time and cost with 2 mode specific dummies (mode 1 and mode 2) which are specified by c and d to take value 1 for a particular mode, Ø for the others.

Any number of such specifications ie 4 variables, 3 modes can be specified and then to terminate ØØØØ will return to specification stage and the model can be respecified or if ØØØØ is typed again on the next line, the program stops. So if a file is defined as channel 2 contained

```
Ø3123190
22 230100282900012600000000
ØØØØ
ØØØØ
```

it would estimate 1 model and then stop.

```
C
      REAL*8 Y(400,3),X(41),EXPLAN(400,30),SUMY(3)
      INTEGER IVV(5),IV(24)
C
      COMMON/VCOM/Y,X,EXPLAN,SUMY,N
C
C
C
  101 FORMAT(I2,I2,I3,I1)
   12 READ(2,101)(IVV(K),K=1,4)
C
      IF(IVV(1).EQ.0) GOTO 13
C
      M=IVV(1)
       NV=IVV(2)
      L=NV/M
      N1=IVV(3)
      NS=IVV(4)
C
  102 FORMAT(50I2)
C
      DO 10 KK=1,100
      READ(2,102)(IV(K),K=1,NV)
C
      IF(IV(1).EQ.0) GOTO 11
C
      WRITE(6,201)(IVV(K),K=1,4)
  201 FORMAT('1',/,1X,'**********MNL ESTIMATION**********',/////,
     * 1X,'NO MODES=',1X,I2,//,1X,'NO VARS=',1X,I2,//,1X,
     * 'NO OBS=',1X,I3,//,1X,'SAMPLE=',1X,I2)
C
       WRITE(6,202)(IV(K),K=1,NV)
  202 FORMAT(///,1X,'VARIABLES USED   ',50I4)
C
      N=0
      MM=0
      DO 2 J=1,M
    2 SUMY(J)=0.0
C
      REWIND 1
      DO 1 I=1,N1
      MM=MM+1
      READ(1,100)(X(K),K=1,41)
    1 CALL MNLV(MM,L,IV,NV,IVV)
  100 FORMAT(F3.0,13F3.0,4F6.2,3F4.1,8F6.2,3F6.2,9F2.0)
C
      WRITE(6,103) N
  103 FORMAT(//,1X,'NO CASES WITHOUT MISSING VALUES=',
     * 1X,I3)
C
      WRITE(6,104)
  104 FORMAT(////,1X,'EXPLAN VARS AND DEP VAR VALUES')
C
      DO 15 I=1,5
      DO 15 J=1,M
      LS=(J-1)*L
      WRITE(6,105)(EXPLAN(I,K+LS),K=1,L),Y(I,J)
   15 CONTINUE
  105 FORMAT(12F8.3)
C
```

```
      CALL MNLWIL(L,M)
C
   10 CONTINUE
   11 GO TO 12
C
   13 STOP
      END
C
C
C
C
C
      SUBROUTINE MNLV(M,L,IV,NV,IVV).
C
      REAL*8 X(41),EXPLAN(400,30),AVAR(400,30),SY(400,3),
     * SUMY(3),Y(400,3),VAR
      INTEGER IVV(5),IV(24)
      COMMON/VCOM/Y,X,EXPLAN,SUMY,N
C
C
C
      IF(X(18).EQ.13) GO TO 10
      IF(X(28).EQ.0.0) GOTO 10
C
      ST=X(2)
      NCR=X(30)
C
      IF(X(18).EQ.9) GOTO 10
C
C     CHECK IF CAR AVAIL SAMPLE
      IF(IVV(4).EQ.1) GOTO 12
C     CHECK IF HEADS SAMPLE
      IF(IVV(4).EQ.2) GOTO 13
C     CHECK IF CAR NOT AVAIL SAMPLE
      IE(IVV(4).EQ.3) GOTO 14
C     CHECK IF NOT HEADS SAMPLE
      IF(IVV(4).EQ.4) GOTO 15
C
      GO TO 11
C
   12 IF(NCR.EQ.13) GOTO 10
      IF(NCR.LT.1) GOTO 10
      GOTO 11
C
   13 IF(ST.GT.1.5) GOTO 10
      GOTO 11
C
   14 IF(NCR.GE.1) GOTO 10
      GOTO 11
C
   15 IF(ST.EQ.13) GOTO 10
      IF(ST.LT.1.5) GOTO 10
C
   11 CONTINUE
      MM=NV/L
C
      DO 1 J=1,MM
    1 SY(M,J)=0.0
C
```

```
      IF(X(18).EQ.5) SY(M,1)=1.0
      IF(X(18).EQ.6) SY(M,1)=1.0
      IF(X(18).EQ.4) SY(M,2)=1.0
      IF(X(18).EQ.1) SY(M,3)=1.0
C
      MM=NV/L
      DO 2 K=1,NV
      II=IV(K)
      IF(II.EQ.0) VAR=0
      IF(II.EQ.1) VAR=1
      IF(II.GT.1) VAR=X(II)
    2 AVAR(M,K)=VAR
C
      DO 3 K=3,L
      DO 3 J=1,MM
      LS=(J-1)*L
      IF(AVAR(M,K+LS).EQ.13) GOTO 10
    3 CONTINUE
C
      N=N+1
C
      DO 4 K=1,NV
    4 EXPLAN(N,K)=AVAR(M,K)
C
      DO 5 J=1,MM
      Y(N,J)=SY(M,J)
      SUMY(J)=SUMY(J)+Y(N,J)
    5 CONTINUE
C
   10 RETURN
      END
C
C
C
```

```
      SUBROUTINE MNLWIL(L,M)
C
C
C    THIS ROUTINE IS MULTINOMIAL LOGIT ESTIMATION
C     FOR THREE MODES
C
C
      REAL*8 AVAR(400,30),X(41),Y(400,3),SXY(30),B(30),
     *EXPLAN(400,30),LCV(3),EXPP(3),PROB(3),DIFF(3),
     *DERV2(30,30),DERVB(30),DERV1(30),SUMY(3),
     *CHANG(30),VARCOV(30,30),INVD2(30,30),SER(30),WKCE(50),
     * SEXP1,PR(400,3),PSUM(3),ELP(3,3),PSQ,PSQA,PSQ1,LLI,
     * LIKE,LIKE1,LIKE2,SEXP,LIKEN,CH(30),XD(30),LLR
C      EQUIVALENCE (EXPLAN(1,1),AVAR(1,1))
C
      COMMON/VCOM/Y,X,EXPLAN,SUMY,N
  101 FORMAT(/1X,'VARIABLES USED= CONST',/(18X,I2))
  102 FORMAT(/1X,'NO. RELEVANT OBS=',1X,I3)
  103 FORMAT(/1X,'NO. ALTS=',1X,I2)
  104 FORMAT(/1X,'SECOND DERIV MATRIX')
  105 FORMAT(/1X,'LOG-LIKLIEHOOD FUNCTION=',2X,F15.5)
  106 FORMAT(/1X,'CURRENT B VALUES='/(18X,F10.3))
  107 FORMAT(/1X,'FIRST DERIVS='/(18X,F15.9))
  108 FORMAT(/1X,'ML ESTIMATES='/(12X,F15.5))
  109 FORMAT(/1X,'INVERSE OF DERV2=')
  110 FORMAT(/1X,'VAR-COVAR MATRIX=')
  111 FORMAT(/1X,'STANDARD ERRORS='/(2X,F10.3))
  112 FORMAT(/1X,'S.E.S=',1X,F10.3,2X,'T-VALUES=',1X,F10.3,4X,
     *'M.L.E.S=',1X,F10.3)
  113 FORMAT(/1X,'ITERATION NO.=',2X,I3)
  114 FORMAT(/,1X,'NO. CHANGED VALUES OF 1ST DERIVS',1X,I3)
C
C
C
C
C   INIIIALISE
C
      DO 3 K=1,L
      B(K)=0.0
    3 SXY(K)=0.0
      ITER=0
C
C
      WRITE(6,102) N
      WRITE(6,103) M
C
      LS=0
      DO 8 I=1,N
      DO 8 K=1,L
      DO 8 J=1,M
      LS=(J-1)*L
      SXY(K)=SXY(K)+EXPLAN(I,K+LS)*Y(I,J)
C      SUMY(J)=SUMY(J)+Y(I,J)
      XD(K)=0.0
      CH(K)=0.0
    8 CONTINUE
   10 CONTINUE
      ITER=ITER+1
      WRITE(6,113) ITER
      NCHANG=0
```

```
      LIKE2=0.0
      LIKE1=0.0
      DO 11 I=1,N
      DO 11 J=1,M
      DO 11 K=1,L
      XD(K)=0.0
      CH(K)=0.0
      CHANG(K)=0.0
      DERVB(K)=0.0
      PSUM(J)=0.0
   11 CONTINUE
      DO 12 K1=1,L
      DO 12 K2=1,L
      XD(K1)=0.0
   12 DERV2(K1,K2)=0.0
C
      DO 31 I=1,N
      DO 32 K=1,M
   32 LCV(K)=0.0
C
      LR=0
      DO 13 K=1,L
      DO 13 J=1,M
      LR=(J-1)*L
      XD(K)=0.0
      LCV(J)=LCV(J)+EXPLAN(I,K+LR)*B(K)
   13 CONTINUE
      SEXP=0.0
      DO 14 J=1,M
   14 EXPP(J)=DEXP(LCV(J))
      DO 15 J=1,M
   15 SEXP=SEXP+EXPP(J)
      SEXP1=SEXP
      DO 16 J=1,M
      PROB(J)=EXPP(J)/SEXP1
      DIFF(J)=(SEXP1-EXPP(J))/SEXP1
      PR(I,J)=PROB(J)
      PSUM(J)=PSUM(J)+PROB(J)
   16 CONTINUE
      DO 33 K=1,L
      DO 33 J=1,M
      LS=(J-1)*L
      XD(K)=XD(K)+EXPLAN(I,K+LS)*PROB(J)
   33 CONTINUE
C
C
      LS=0
      DO 17 K1=1,L
      DO 17 K2=1,L
      DO 17 J1=1,M
      LS=(J1-1)*L
      NEG=-1.0
C      DERV2(K1,K2)=DERV2(K1,K2)-EXPLAN(I,K1+LS)*
C     * EXPLAN(I,K2+LS)*PROB(J1)*DIFF(J1)
      DERV2(K1,K2)=DERV2(K1,K2)-(EXPLAN(I,K1+LS)-XD(K1))*
     * PROB(J1)*(EXPLAN(I,K2+LS)-XD(K2))
   17 CONTINUE
      LS=0
      DO 18 K=1,L
```

```
      DO 18 J=1,M
      LS=(J-1)*L
      DERVB(K)=DERVB(K)+EXPLAN(I,K+LS)*PROB(J)
C      CH(K)=CH(K)+XD(K)*(Y(I,J)-PROB(J))
      CH(K)=CH(K)+(EXPLAN(I,K+LS)-XD(K))*(Y(I,J)-PROB(J))
   18 CONTINUE
      DO 19 J=1,M
   19 LIKE2=LIKE2+Y(I,J)*DLOG(SEXP1)
   31 CONTINUE
C
      WRITE(6,104)
C
      DO 20 K=1,L
      DERV1(K)=SXY(K)-DERVB(K)
      LIKE1=LIKE1+SXY(K)*B(K)
      WRITE(6,210) (DERV2(K1,K),K1=1,L)
   20 CONTINUE
      LIKE=LIKE1-LIKE2
      IF(ITER.EQ.1) LIKEN=LIKE
      WRITE(6,105) LIKE
      WRITE(6,107)(DERV1(K),K=1,L)
      IF(ITER.GT.25) GOTO 30
      ID=30
      IV=30
      NA=L
      IFAIL=0
      CALL F01AAF(DERV2,ID,NA,INVD2,IV,WKCE,IFAIL)
C
      IF(IFAIL.EQ.1) GOTO 50
   30 CONTINUE
      DO 21 K1=1,L
      DO 21 K2=1,L
C  21  CHANG(K1)=CHANG(K1)+INVD2(K1,K2)*(DERV1(K2)-CH(K2))
C   21 CHANG(K1)=CHANG(K1)+INVD2(K1,K2)*CH(K2)
   21 CHANG(K1)=CHANG(K1)+INVD2(K1,K2)*DERV1(K2)
      DO 22 K=1,L
      B(K)=B(K)-CHANG(K)
C      B(K)=B(K)+CHANG(K)
   22 IF(DABS(CHANG(K)).GE.0.0000000005) NCHANG=NCHANG+1
      WRITE(6,114)NCHANG
      WRITE(6,106) (B(K),K=1,L)
      IF(NCHANG.EQ.0) GOTO 23
      IF(ITER.GT.15) GO TO 50
C      IF(ITER.EQ.2) UPPER=X(61)
      GO TO 10
   23 WRITE(6,108) (B(K),K=1,L)
      WRITE(6,109)
      DO 27 K2=1,L
   27 WRITE(6,210)(INVD2(K1,K2),K1=1,L)
      DO 25 K1=1,L
      DO 25 K2=1,L
   25 VARCOV(K1,K2)=-1*INVD2(K1,K2)
      WRITE(6,110)
      DO 28 K2=1,L
   28 WRITE(6,210)(VARCOV(K1,K2),K1=1,L)
  210 FORMAT(2X,20F15.5)
      DO 26 K=1,L
      SER(K)=DSQRT(VARCOV(K,K))
      UPPER=B(K)+1.96*SER(K)
```

```
      LOWER=B(K)-1.96*SER(K)
      TVAL=B(K)/SER(K)
      WRITE(6,112) SER(K),TVAL,B(K)
   26 CONTINUE
C
      WRITE(6,120)LIKEN
  120 FORMAT(//,1X,'LOG LIKE AT B(0)=',F10.4)
C
C
C
      LLR=-2*(LIKEN-LIKE)
      WRITE(6,121)LLR,L
  121 FORMAT(//,1X,'LOG LIKE RATIO=',F8.3,5X,'DOF=',I3)
      PSQ=1-(LIKE/LIKEN)
      WRITE(6,122)PSQ
  122 FORMAT(//,1X,'P SQUARED=',F8.3)
      PSQA=1-((LIKE/(N*(M-1)-L))/(LIKEN/(N*(M-1))))
       WRITE(6,123) PSQA
  123 FORMAT(//,1X,'P SQUARED DOF ADJ =',F8.3)
      PSQ1=1-DEXP((LIKE-LIKEN)*(-2/N))
      WRITE(6,124) PSQ1
  124 FORMAT(//,1X,' PSEUDO R SQUARED=',F8.3)
C
      NP=0
      DO 40 J=1,M
      NP=NP+1
      PPSUM=PSUM(J)/N
      PSUMY=SUMY(J)/N
   40 WRITE(6,125) NP,PPSUM,PSUMY
  125 FORMAT(//,1X,'MODE ',I4,2X,'AV PROB=',F8.3,4X,
     * 'OBSERVED PROP=',F8.3)
C
   50 RETURN
      END
```

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