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Models of consumer shopping behaviour in urban areas

MODELS OF CONSUMER SHOPPING BEHAVIOUR

IN URBAN AREAS:

Analysis of the Cardiff Consumer Panel

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Memorandum

This thesis is the original work of the candidate except where acknowledgement is given, and has not been submitted for a degree in this or any other University

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ABSTRACT

Scope

The behaviour and activity of consumers is studied. Attention is given to the decisions and movements of shoppers, especially those aspects which are repeatedly associated with the purchase of grocery goods. The approach is empirical and seeks insights into how consumers behave. All substantive findings are derived from the Cardiff Consumer Panel (1982).

Three questions are asked at the outset: (1) how clean are the data? (2) what themes are apparent from the data? (3) can these themes be summarised and integrated? Corresponding to these questions are three major areas of research: methodology, description and modelling.

1 Methodology

The analysis of methodology shows how the consumer panel is an appropriate source of data for the study of behaviour and activity. If findings are to be relied upon careful quality control is needed at an early stage. Several tests are applied to show that the Cardiff Consumer Panel is a reliable data-base.

2 Description

Simple tables and graphs summarise features of behaviour. Consideration is given to trip frequencies, temporal rhythms, and movements through the city. The impact on shopping of family, work and mobility is stressed.

3 Modelling

Formal models are introduced to make description more disciplined and effective.

Classification is undertaken to explore the data and to identify major patterns. The adaptation of cross-sectional models is considered next, and a distinction is made between the incidence of events and the choice of alternatives. Finally, an integrated approach is illustrated. The integrated approach is able to handle repeated choices and the repeated occurrence of activity patterns. All models are evaluated. Model sensitivity, diagnostics, omitted variables, heterogeneity and temporal dependence are scrutinised.

Themes

Three themes underlie all sections of the thesis. (1) Single components of behaviour cannot be studied in isolation from other activities which occur in time and space. (2) The operational task of data description must involve an assessment of data/model quality. (3) Insights gained from longitudinal methods are richer than those from cross-sectional approaches. Extensions are discussed at the end of each major section.

Key Words

activity analysis
beta-logistic models
Cardiff
choice models
classification
incidence models
longitudinal analysis
model assessment
panel methodology
quality control
retailing
shopper behaviour
space-time studies
urban travel

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DETAILED CONTENTS

INTRODUCTION

Viewed in a time-space perspective, then, we have two diverse systems in interaction. One is the predominantly time-directed warp of individual life-paths ... The other is the more space-oriented set of imposed constraints of domains and bundles to which the individual may or may not have access according to his needs and wants.

Torsten Hägerstrand (1970)
'What about People in Regional Science?'

1 Preamble

Imagine that a study has been devised to trace the movements of a single shopper over several weeks. The shopper lives in a prosperous suburban community and works part-time in the central business district (figure 1.1). She gazes out of the office window; other shoppers are seen passing from chemist to florist, some cross the road to a travel agency. The street scene appears to be confused.

During the surveillance period our shopper visits about one dozen different shops. All these shops are situated within the central area or at a district centre lying to the north. These nodes in the shopper's activity space define a narrow domain of movement. There are, then, sharply defined personal limits to what often looks like a scene of general confusion.

A detailed record is kept of when and how shops are visited. On Monday (d_1) at 11 am (t_2) the shopper leaves home (P_4) and rides to work. After alighting from the bus she buys some vegetables at a market stall. The next evening she drives to the district centre and buys meat at a superstore. These sequences of movement describe daily paths of activity.

Maps and descriptions of personal movement reveal how some features are repetitive and habitual. If our shopper was to glance out of her office window at about the same time every week she might always see a man going into the chemist.

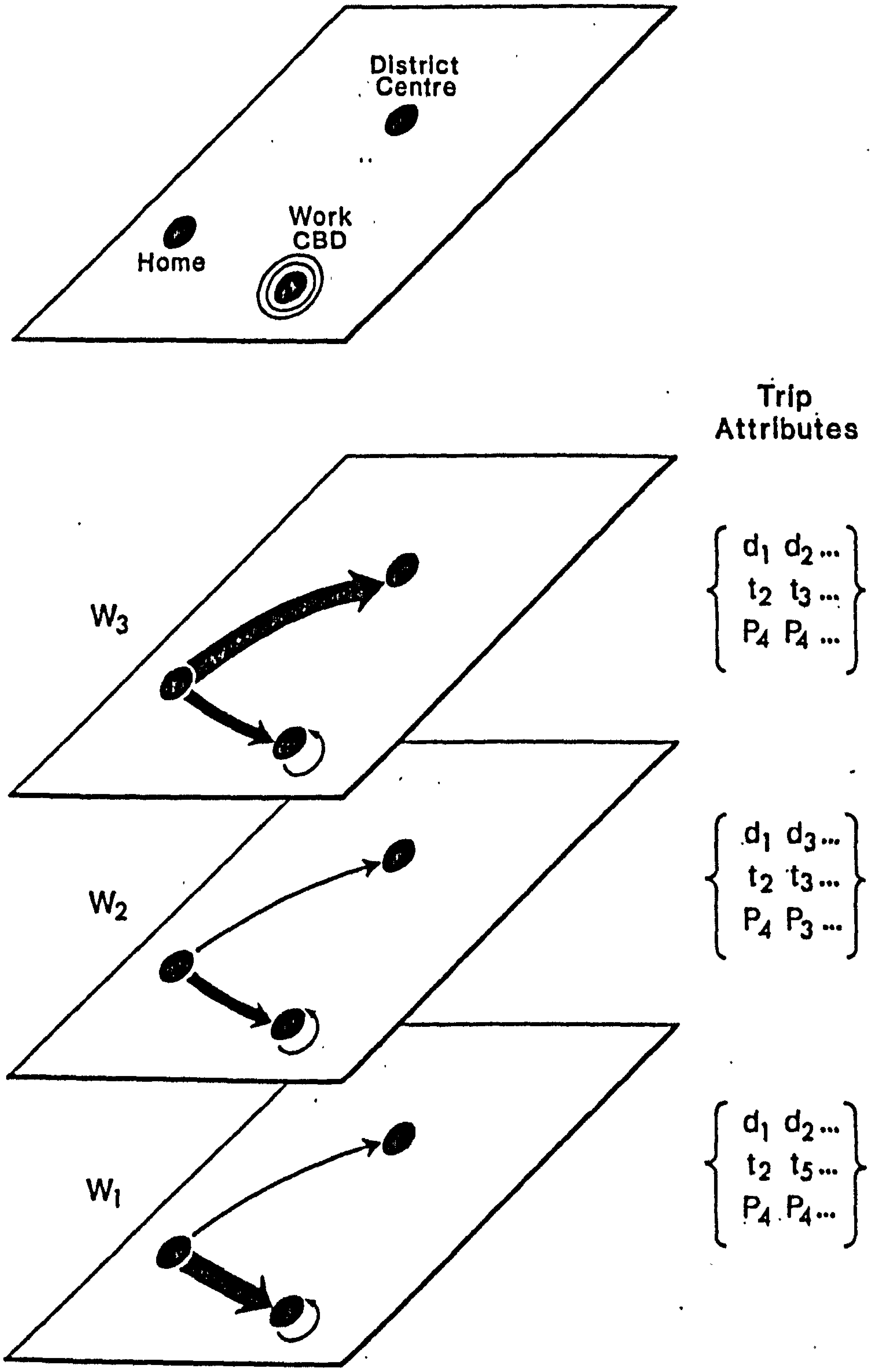
Consider her own record of movement: on Wednesday (d_3) the shopper leaves her job (P_3) at noon (t_3) to buy cakes from a baker's shop, and these visits recur each week ($W_1, W_2, \ldots$). This recurrent pattern is depicted in figure 1.1 as a loop around the central business district. If we ask why cakes are bought at the same place we might be told about their quality, the cleanliness of the premises, or the friendliness of the sales staff; for whatever reason a pattern of loyalty is observed. Not everything is as confused as we originally thought.

More than likely loyalty arises because of imperfect knowledge. Most people are familiar with a limited number of places within any city, and places outside the local turf are unperceived or feared. Even within the subset of places that are known to a person there are further controls over everyday movement.

Selection of a destination, or participation in an activity, depends on travel time, prices and fares, the need to pack together several activities on one trip, opening times, and the degree to which decisions are made jointly with other people. In short, participation in one activity depends on how the whole programme of other activities is arranged in time and space.

Figure 1.1

Trips Recorded by a Single Shopper Over Three Weeks



W week
d day
t time
p previous activity

The amount of discretion that is available to a shopper varies greatly. Many constraints are rigidly imposed by authorities and institutions, such as shop trading hours and hours of work. Perhaps cakes are bought at the nearby bakery during Wednesday lunchtimes because the shop closes after 2 pm or because this is the only shop that can be reached during the lunch-break. Loyalty to a shop may be a sign of necessity. Similarly, trips undertaken using public transport are regulated by fixed timetables and by the position of bus stops or metro stations.

Family living restricts discretionary activity too. To do something together, members of the family must be at the same place at the same time. Precisely where and when family members are brought together will be a matter for negotiation, and will be subject to other calls on people's time. Recall that on Tuesday (d_2) of week one meat was bought at a superstore; access to the family car made this trip possible. Such a situation is common: participation in an activity depends on the availability of shared goods, and implies that other members of the household share in the same activity or that they are willing to forego choices themselves.

An old couple is seen from the office window, they are struggling with an awkward basket of goods. Infirmity and health, in fact, are crucial regulators of movement and activity. To walk with a basket of groceries narrows the activity space considerably, since only corner shops and neighbourhood stores are accessible. Access to a car means that shoppers can reach more distant destinations almost regardless of physical health: physical constraints exist but technology reduces their impact.

Remember that view from the office window? Perhaps we can begin to make it more intelligible.

First, many aspects of individual behaviour are not really confused. The activity spaces within which shoppers move and work are tightly bounded. These bounds arise because activities have to be packed into the confines of available time and space; confines which themselves are governed by organisations, families, personal capabilities and the current state of technology. As a result there is a tendency to do what is familiar and comforting, and revealed behaviour becomes repetitive.

Second, as more shoppers are brought into the scene the general impression becomes <u>more orderly</u>, not less. Again and again, shoppers who live under different specific conditions behave in a similar manner. This does not mean that all people are alike in every respect; but there are marked regularities in everyday behaviour. Many influences that act upon an individual hold true for groups of people; thus, access to technology and the definition of family roles are aspects of life that operate at both personal and societal levels.

Orderliness means that we can communicate something about what is seen from the vantage point of the office window to those whose concerns are practical. We can be more precise than saying: 'it's a busy street scene'. It is possible to say: how busy, how much money is spent, whether the same shops are visited repeatedly, and whether people normally travel by car. These patterns of consumer behaviour give us an understanding of how people behave which ought to be of benefit to marketers, consumers, planners and other urban researchers.

This thesis is an account of how consumers behave in a typical British city. Described and summarised are the movements and choices that consumers make everyday when they shop for grocery goods. While the structure of revealed behaviour arises from the interplay between perceptions and societal rules, the questions asked in this thesis are practical and require empirical answers.

Data analysis is a central theme, and it is the role of data analysis which distinguishes this work from several alternative accounts. In particular, structural reasons to explain why everyday activity occurs in the way it does are not considered; though our knowledge of these reasons is being enriched by the work of Giddens (1979), Carlstein (1982) and Thrift (1983). Nor is there an attempt to empathise with what it means to experience the drudgery of shopping; though several anthropological studies show the fascination of such an approach (Rowles 1978, Carlstein 1982). All three approaches - the empirical, structural, and anthropological - share a common desire to study routine and repetitive behaviour where the bounds of space and time are interlinked.

In the remainder of the introduction it is shown how panel data are suitable for the study of consumer behaviour and activity. The introduction ends with an outline of the thesis.

2 Consumer Panels

Empirical research in geography has predominantly relied upon cross-sectional surveys and questionnaires. These surveys often provide snapshot views of urban life. Like sepia prints of Edwardian society the views are often full of fascinating detail, and yet there is little sense of movement, recurrence, or impending change. Panel surveys that trace the movements and decisions of consumers through time and space are a departure from such static surveys. To continue the photographic metaphor, panels bring us nearer to the era of the movies and cinéma vérité.

In this section the origins of consumer panels are discussed, and an appraisal of their utility is presented. Consumer panels are shown to be an excellent source for many types of investigation in the social sciences, and their particular relevance for the study of shopping activity, personal movement, and space-time paths is justified.

2.1 Development

The origins of panel-based research lie in the social survey work of Meyhew and Rowntree and in the studies of daily routine that were done by Strumilin. All these observers sought to document the quality of life of ordinary folk. It was not until the mid-1930s that formal panels began to appear. These early panels were used to investigate reactions to radio programmes and voting behaviour, and also continued to focus upon the study of people's lifestyles and routine activities (Lazarsfeld 1948, Moser 1950).

During the 1940s several commercial and official government panels came into operation. Typically, regular events were recorded in self-completion diaries. Coverage was often limited to the purchase of grocery goods, toiletries and cosmetics; although medical and life-cycle events began to be documented too. The impetus for this form of social research came from advertisers and brand-managers, and from those who administered war-time rationing schemes. In particular, official surveys such as the National Food Survey, the Family Expenditure Survey, and the longitudinal studies of child development were instigated in order to assist war-time and post-war planning.

Over the next couple of decades many commercial ventures were consolidated. Included in the list of these early panels are several which remain important today, such as those operated by A. C. Nielsen, the Market Research Corporation of America (MRCA), Attwood Statistics, AGB Research, and GFK-Nurnberg. Increasingly, panel design and methodological problems were examined. Many of these problems were familiar from cross-sectional surveys (sample bias and data processing for instance), others were peculiar to the design of longitudinal surveys (especially the loss of respondents and the conditioning of their behaviour) (Ehrenberg 1960, Sudman 1964a, 1964b, Buck 1982).

Today commercial consumer panels are large-scale, national and weekly. Mail-delivered diaries are used to collect information about the purchase of grocery and convenience goods. Throughout the western world commercial agencies maintain these panels with an average size of 4,000 participants (Sudman and Ferber 1979). The type of analysis performed on these data has been influenced by the historical legacy. Loyalty to brands, for instance, has been researched in depth; rather than loyalty to shops, or to forms of travel, or to routes through a city.

While results from brand-purchase panels have attracted much commercial interest, most people are familiar with this form of survey research because of measurements of television audiences. The JICTAR and BARB records are good examples of continuous monitoring of behaviour (see Ehrenberg and Twyman 1967). Both brand and television studies have an important role in marketing and the media, and this is well known, but these studies are not the only applications of panel survey methods. Aspects of medicine and health, transport and activity, labour economics and income, migration and movement have all been investigated using methods that are essentially similar.

Often non-commercial panels are ad hoc and only last a few weeks or months. There are, however, some worthy exceptions in medical, epidemiological, and labour studies. The Institute of Child Health keeps records of the physical growth and medical history of children, and has done so for many years. Likewise, a continuing source of labour, income, occupation and migration data is contained in the Michigan Panel Study of Income Dynamics. While these records appear to be very different - some take the form of event histories for cohorts of a population and are not strictly panels - many principles and many models remain unchanged.

Finally, the contribution of time-budget surveys should be noted. These maintain the tradition of detailed observation of routine behaviour. Time-budget surveys tend to be client-based and extremely detailed, therefore it is rare for a survey to last more than one week. European traffic planners, in particular, have made use of budgeting information to improve public transport services, to reduce waiting times and to improve traffic flows.

The most ambitious projects were the International Time Budget Study (Szalai et al. 1972) and the Washington-area activity study (Chapin 1974). Both these projects investigated how people arranged their activities in time and space; the former worked at a cross-national scale and the latter involved the comparison of sub-groups within a single urban area.

Panel data appear in many different fields of research. Seemingly unrelated studies of brand management, broadcasting and public transport share a need for data that is collected from a panel. Not all these are operated in exactly the same way, but many of the methodological and analytical issues are similar. Much of this material is beginning to enter geography.

2.2 Advantages

Consumer panels have a number of advantages over other forms of mass survey. These advantages arise because of the innate qualities of the method and because certain types of information cannot be obtained in any other way.

The innate qualities of the panel method are listed as follows:

- Events are recorded in detail at a micro scale.

- It is a cost effective way to collect data that describe frequent and recurrent behaviour.

- The whole longitudinal record is maintained for the same group of people, so the sample is only recruited once.

- Precision is achieved because people are asked the same questions time and again; under stable conditions the variance of responses should be low.

- The methodology has been thoroughly tested over several decades.

- When the diary-completion method is used less reliance is placed on memory recall, this means that the source is more accurate.

The last point is perhaps the most important and it needs to be elaborated. Traditional questionnaire methods suffer from three sources of inaccuracy:

(1) recall loss
(2) recall distortion
(3) telescoping

Recall loss occurs when recollection of an event is imperfect and when details are forgotten. Often recall loss operates in a systematic manner: minor events are understated or ignored altogether. Recall distortion arises when respondents provide an ex post justification of their behaviour in order to please the interviewer. Finally, the tendency to over-report the number of events within a recall period is called telescoping.

Consumers who complete diaries, by contrast, are trained to record purchase details as they happen. Immediate record-keeping minimises the problems of recall loss and telescoping. It means, for instance, that walking trips and visits to small stores are recorded more accurately, just like records of major shopping expeditions. Moreover, when diaries are completed routinely and automatically recall distortion is less likely to occur. Panels that depend upon the diary-completion method are generally likely to provide an accurate record of how consumers behave.

To the list of innate advantages must be added the fact that certain types of information cannot be obtained in any other way:

- The incidence of events can be related to consumer variability; retail audits do not permit such study.

- In models where panel data are used, spurious statistical effects can be separated from true effects; this is not possible with cross-sectional approaches.

- It is possible to identify norms, to track changes and trends, and to study the sequencing of events; time-budget surveys might gather similar information but they do not last long enough to confirm these patterns.

- Panel methods facilitate the study of temporal processes, repetition, habit and dynamics; without such data researchers have to rely upon contrived examples and simulation studies.

Overall, panels are a reliable and precise source, and they have the potential to give detailed insights into how consumers behave. Several studies have attempted to measure the superiority of panel/diary methods over cross-sectional surveys. Results show that the direct recording of events in diaries is far superior to surveys that rely upon respondent recall (Parfitt 1967, Sudman and Ferber 1979, Wind and Lerner 1979, Heggie 1983, Coleman 1981).

Moreover, bias associated with respondent recall is systematic: there is a tendency to overstate nationally advertised brands and frequently patronised stores. The magnitude of bias is indirectly related to a brand's penetration of a product field and a store's penetration of a trade area. Panel/diary methods are not biased in these ways.

2.3 Activity Research

Despite the wealth of material that is available from commercial sources, geographers and planners have not tapped these data. There are important reasons why the direct transfer of commercial consumer panel data into geographical research is not possible:

(1) In an attempt to be representative of the whole population commercial panels draw on national random samples. These sampling frames cover a wide area, so very few members live near each other and hardly any are exposed to the same range of retail opportunities (Wrigley 1980, 57).

(2) Commercial panels are designed to collect brand data; rarely is shop type or shop location recorded, and information about travel to reach shops is excluded altogether.

(3) Most commercial panels are run for a continuous syndicate, to which individual companies subscribe and over which individual researchers have little operational control. There are related problems to do with the cost of subscriptions, the commercial value of results, and the confidentiality of data.

(4) The sample size and sample representativeness of mature panels is often preserved using dynamic recruitment. Those members of the panel who out-migrate or die are replaced by newly formed households and in-migrants. Dynamic sampling is essential if mature panels are to remain viable, but in disaggregate geographical research it may be wholly inappropriate.

Notwithstanding the difficulties, a good number of consumer panels have been employed to study geographical issues. The majority have been ad hoc and non-commercial. In designing these panels special attention has been given to areal sampling schemes, the location of shops and distances from homes, and to the collection of travel/time-budget data.

Listed in table 2.1 are many of the panels that have addressed issues of geographic interest. The list is not exhaustive, but it is sufficiently complete for a number of generalisations to be drawn:

(1) Most panels do not last more than one week. Where records are kept over several weeks the sample size is commensurately smaller. In fact there is an inverse relationship between the length of observation period and sample size: compare, for example, the Bradford survey (102 households monitored over 20 weeks) with the Brent Cross study (about 1700 households over 1 week).

(2) Run-in periods are short. Only three panels can be regarded as having any form of run-in period (Bradford, Cardiff, and Lancashire/London). Usual commercial practice is to discard the first two weeks of a panel because the sheer novelty of participation conditions the behaviour of respondents. Furthermore, response error problems are more likely whilst the respondent is learning to complete diaries accurately. Most geographical panels, therefore, operate within a period when conditioning and response error are liable to be severe, and have finished before routine behaviour has been re-established.

Table 2.1

Consumer Panels in Geographical Research

Location (alphabetical order)	Date of Survey	Length of Panel	Size of Panel (final size) (1)	Reference/Sponsor/Collaborators (description)
Baltimore, Maryland	1977	1 week	236 travellers (rotated)	Pas (1984), Hanson (pc). COMIS Corporation and US Department of Transportation (daily activity patterns)
Banbury, Oxon.	1975-76	1 week	72 individuals (rotated)	Jones et al. (1983). Transport Studies Unit and Social Science Research Council (all activities, travel and locations)
Bradford, West Yorks.	1968	20 weeks	102 households	Norman (1968) and Wrigley (1980). Management Centre, University of Bradford (consumer purchases and shop types)
Brent Cross, North London	1976/78	1 week	1707 consumers	Bruce and Mann (1977). Greater London Council (before/after grocery-store)
Bretton, Peterborough	1972	4 weeks	172 consumers	Rogers (1974) Retail Outlets Research Unit and Sainsbury (before/after grocery-store)
Brighton, Sussex	1972	1 week	1074/851 households (rotated)	Vickerman and Barmby (1984) Department of the Environment (purchases, expenditure and travel)

Table 2.1 (cont.)

Bristol, Avon	1970	10 weeks	89 students	Hudson (1974) Economic and Social Research Council (acquisition of grocery-shop knowledge)
Cedar Rapids, Iowa	1949	30 days	116 travellers	Marble and Bowlby (1968) Traffic Audit Bureau (shopping patterns)
Coventry, Warwick.	1969	1 week	487 individuals	Davies (1973) Coventry City Planning Department, Sainsbury and Marks & Spencer (convenience and durable shopping)
Haifa, Israel	1983	1 week	567 (288) individuals (households)	Hirsh et al. (1984) Transportation Research Institute, Technion (travel and shopping activity)
Halifax, Nova Scotia	1971-72	weekdays	1561 individuals (rotated)	Janelle and Goodchild (1983) Institute of Public Affairs, Dalhousie University (space-time activity patterns)
Hamilton, Ontario	1978	2 weeks	704 households	O'Kelly (1983a) Social Sciences and Humanities Research Canada and McMaster University (travel and activity)
Lancashire/ London	1980s	24 weeks	800-900 households (each area)	Kau and Ehrenberg (1984) AGB Research UK and commercial sponsors (consumer behaviour, purchasing and shop types)
M62, West Yorks.	1970			Bamford and Judge (1972) Motorway Economic Impact Study and Institute for Transport Studies, Leeds University (trip generation and travel patterns)

Table 2.1 (cont.)

Reading/ Leicester	1972	1 week	10% of student body	Bullock et al. (1974) Martin Centre Cambridge University and Department of Education and Science (all activities in and out of home)
Reading, Berks.	1973	1 week	450 individuals	Bullock et al. (1974) Martin Centre Cambridge University, Social Science Research Council, Social and Community Planning Research (all activities)
Santa Barbara, California	1984	4 weeks	194 households	Golledge and Wrigley (1983) US National Science Foundation (consumer behaviour, attitudes, perceptions)
Sydney, Australia	1981-85	4 waves	1436 households	Hensher and Wrigley (1985) Australian National Energy Research Development and Demonstration Program (demand for vehicles: holdings, transactions and usage)
Uppsala, Sweden	1971	5 weeks	296 households	Hanson and Hanson (1980) (all activity outside home)
Watford, Herts.	1969	1 week	1672 consumers	Daws and McCulloch (1974) Building Research Establishment and AGB Research UK (consumer travel and shopping activity)
Cardiff, Wales	1982	24 weeks	451 households	Guy et al. (1983), Wrigley et al. (1985) Economic and Social Research Council, Research and Marketing (Wales and the West) Ltd. (consumer behaviour and travel)

(1) Respondents may keep a diary for only one day and these single records may be aggregated to provide weekly diaries. Such panels are said to be 'rotated'.

(3) The quality of results will be affected by the resource base (in terms of previous experience, finance, and the limited time in which to do pilot work, prepare briefs, collect diaries, and check and code diary sheets). Several independent researchers have responded by working with students (such was the case at Bristol, Reading and Leicester) or by collaborating with retailers (as at Bretton and Coventry). The collection of data for two of the largest surveys was undertaken by AGB Research: the Watford study was specially commissioned by the Building Research Establishment, whereas the Lancashire/London studies tapped existing sources.

If previous research has shown the potential of panels for the geographer, the future outlook is even brighter. The automation of data gathering is one reason to expect renewed interest. Now it is possible to collect consumer data at the point-of-sale: when a shopper checks-out at a supermarket a personal identification number is keyed into a terminal, then the bar code on each product is scanned. These automated records will come to displace the diaries so laboriously kept in the past. Already trials have been conducted at AGB Research, the Market Research Corporation of America, and by Management Decisions Systems.

Innovations are not confined to automation in-store: many aspects of travel and traffic are also being monitored in novel and better ways. Under the auspices of the Services and Methods Demonstration Program, operated by the Transportation Systems Centre in Washington DC, comprehensive intra-urban panel surveys are being organised. There is definite potential for geographical studies based upon these travel surveys.

Lastly, greater awareness of panel methods is to be expected because of their association with the communications revolution. Automated monitoring, on-line access to information, and rapid processing of data enable results to be disseminated faster. These changes, together with innovations in broadcasting and telecommunications, will alter the very patterns of behaviour that we seek to describe.

Three implications follow from the review of consumer panels in activity research:

(a) Geographers need to be actively involved at the design stage. If distance and activity data are to be collected routinely then the practical utility of such information should be demonstrated to those who plan and execute major panels.

(b) Quality control is crucial. This applies at the stage of panel design and during panel administration, but continues to be important when data are described and when results are communicated to users.

(c) For the purposes of geographical research there is a need to broaden the compass of our definitions; to look beyond the choice of products, brands and shops and to consider the movements and activities of shoppers. The choice of shop is determined in part by the goods on offer and their prices, and also by how easy it is to reach the shop and how shopping can be packed into a schedule of other activities.

A response to some of these potentials and implications is provided in the pages that follow, and it is to the structure of this response that attention is turned.

3 Structure of the Thesis

The behaviour and activity of consumers is studied. Attention is given to the decisions and movements of shoppers, especially those aspects which are repeatedly associated with the purchase of grocery goods. The approach is empirical and is designed to seek insights into how consumers behave.

To study these themes, three major areas of research are developed: methodology, description and modelling. These areas of research are interrelated to the extent that results from one section are contingent upon results from another section (figure 3.1). The nature of each section is appreciated if we ask three questions:

1 are the data reliable ?

2 what themes are apparent from the data ?

3 can these themes be summarised and integrated ?

The first question refers to the quality and cleanliness of the data, and this is addressed in chapter 1. The chapter starts with an introduction to the Cardiff consumer panel and a brief account of retailing in the city of Cardiff. The first of the formal analyses is presented in section 3 of chapter 1. Biases that arise during panel recruitment and during the course of panel operation are examined. Those problems which are peculiar to longitudinal data deserve greater scrutiny, therefore the chapter concludes with studies of temporal stability and repetition. This appraisal of methodology gives us the confidence to rely upon the panel data at a later stage.

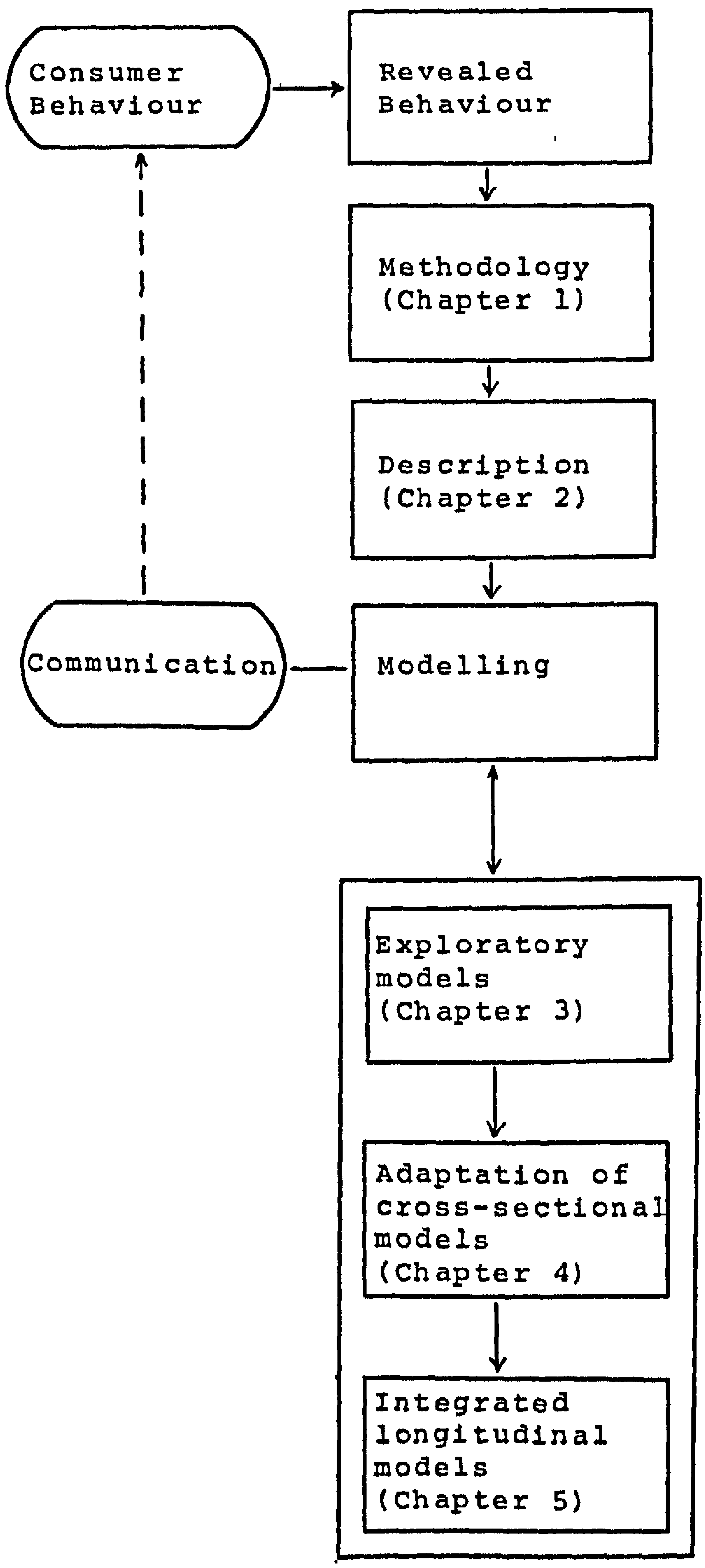
What themes are apparent from the data ? This second question directs us to the description of data. In chapter 2 simple tables and graphs are presented to summarise the main features of behaviour and movement. Consideration is given to trip frequencies, temporal rhythms and travel to shops in section 2.1. Sections 2.2 and 2.3 are then designed to explore how behaviour is influenced by the personal circumstances of consumers.

Simple descriptions are used to compare findings from Cardiff with those collected from earlier surveys. More broadly, these studies can assist in the formulation of policy, they highlight topics that are worthy of further investigation, and they help the analyst to calibrate models.

Chapter 2 goes some way to summarise the important features of the data; however, for many purposes we require an approach that is more structured and formal. In seeking to answer the third question - can these themes be summarised and integrated ? - attention is turned to modelling.

Figure 3.1

Structure of the Thesis



Data

1. Are the data reliable ?

2. What themes are apparent from the data ?

3. Can these themes be summarised and integrated ?

1. Principles

2. Substance

3. Assessment

4. Extensions

There are several powerful reasons why we should turn to models:

- to reduce the volume of data and, thereby, to isolate the salient features of consumer activity
- to identify associations between the components of activity and to assess the strength of associations
- to provide an holistic view of temporal and spatial processes

Modelling is an effective way to analyse data and, ultimately, it makes communication easier. Some graffiti that I read at a Regional Science Conference summed up my viewpoint very aptly: 'models are a disciplined way to tell a story'.

Applied issues are stressed in these model-oriented chapters. Abstract and non-operational theories are deliberately given less weight. It is recognised that there are many perceptual and cognitive notions which might underlie observed behaviour (such as utility, beliefs, learning, intentions, inhibitions and fantasies). Indeed, there will be a degree of isomorphism between abstract concepts, models and 'real' human processes. The philosophical nature of this isomorphism is not investigated in this thesis.

When the search is for subliminal processes non-modelling strategies are to be preferred (for example role-playing exercises and in-depth qualitative research would seem to be appropriate). Models are best confined to the exploration and summary of data, that way they will help to tell a story.

This attitude to modelling forms a backdrop to chapters 3, 4 and 5. These chapters are organised around two natural sequences: between chapters there is a steady rise in the amount of structure that is imposed on the data; within every chapter the progression is from basic principles, through substantive findings, to model assessment and extensions (figure 3.1).

The classification of consumer activity is studied first (chapter 3). The main aim is to elicit the salient features of panel data without imposing too many preconditions, assumptions or constraints. Classification provides a fairly uninhibited 'first look'.

The adaptation of cross-section and regression-type models is considered next. A distinction is made between the incidence of events and the choice of alternatives (chapter 4). At this stage a number of parametric assumptions are made about the distribution of random components. A definite structure is imposed on the data and behavioural responses are expected to depend on observed variables.

Finally, an integrated approach is set forth in chapter 5. The integrated model handles repeated states; these states refer to the choice of travel mode, the timing of purchases, and the number of occasions when a particular bundle of shopping activities is observed. Further parametric assumptions are imposed and the specification of these integrated models is more complex than hitherto.

A second sequence of organising principles runs throughout each chapter:

1 principles

2 substance

3 assessment

4 extensions

Methods are introduced step-by-step and in each case simple geographic studies are used to illustrate the basic principles. The Cardiff consumer panel provides all the material for the substantive work, and results are summarised through a series of examples. These examples refer to travel and scheduling decisions, such as the choice of travel mode and the decision to combine shop visits with other family maintenance activities.

The next step is to assess the findings. Many issues could be studied: sensitivity and robustness, specifications and transformations, model comparison, and spatial and temporal dependence. Here the approach is selective; the focus is upon some of the more innovative tests and those most suited to panel data. This involves the analysis of stability and sensitivity. The integrated approach of chapter 6 also enables temporal effects to be appraised, including the effects of omitted variables and heterogeneity, feedback and temporal dependence.

Tests of a model serve a dual purpose. Essentially they should validate the substantive findings and help us to refine the model. A more fundamental purpose is to lay down a challenge for future research: statistical 'problems' beget geographical 'resources'. In recognition of these challenges each chapter concludes with comments that are tentative and speculative. A wider literature is drawn into the discussion and it becomes evident that there are many opportunities for grafting together ideas from disciplines as diverse as biomedical science, econometrics and marketing.

The main theme, then, is the description of consumer behaviour. Shopping activity and travel to shops are studied in depth. An important sub-theme is the need to make an assessment of data/model quality, and to do this at every stage of an investigation (from initial survey work to the specification of robust models). Another sub-theme is the desire to develop models that are simple and transparent.

This thesis does not have a definite prescriptive or normative role. The occasional reference to policy issues hints at what has been studied, what might be examined, and how the findings presented here might be relevant. Several issues that affect public policy, management and planning are noted, such as the revision of shop opening hours, the provision of public transport and access to stores, novel forms of retailing and physical distribution. In general, however, I share the sentiments that Margaret Drabble describes when she writes: 'Dickens evokes the fog, but does not add a lecture on air pollution'.

PART I

METHODOLOGY and DESCRIPTION

The Cardiff consumer panel is introduced and the basic features are described.

The first two sections of chapter 1 provide background information. Sufficient information is presented so that the nature of the panel and the character of Cardiff can be appreciated. It is important to be aware of why the panel survey was undertaken because decisions taken at the planning stage influence what can be done later. Likewise it is necessary to know something about the retail environment, only then can people's behaviour be seen in an appropriate context.

The first of the formal analyses is presented in section 1.3. Potential methodological problems are studied, and special attention is given to those problems which are peculiar to longitudinal data. The study of methodology is crucial: subsequent research depends upon the existence of sound input data.

In chapter 2 several descriptions are presented. Section 2.1 summarises the basic features of consumer behaviour in space and time, including: movement, shopping frequencies, temporal rhythms, and the pursuit of related activities. Sections 2.2 and 2.3 explore how behaviour is influenced by the personal circumstances of consumers.

Attention is focussed on family and work, and aspects of space and mobility. Temporal patterns and social constraints are emphasised in section 2.2. In section 2.3 forms of travel, access, distance and the location of destinations are studied.

Apart from the findings that are of substantive and comparative interest, two lessons are drawn from Part I. First, quality control is necessary throughout a research project: elaborate sensitivity analysis of complex models is of little practical use if the input data are inaccurate. Second, simple descriptions should precede complex modelling exercises. These descriptions will bring to the fore topics that are worth exploring in greater depth, they will enable current studies to be cross-referenced against earlier studies, and they will help the analyst to calibrate formal models.

CHAPTER 1

THE CARDIFF CONSUMER PANEL

No questions, however precise, can substitute for inability to remember accurately. As the average housewife just does not know accurately she obviously cannot say accurately.

John Parfitt (1967)
Journal of Advertising Research

1. Operation of the Cardiff Consumer Panel

The operation of the Cardiff consumer panel has been described already by the principal investigators (see Guy et al. 1983, and Wrigley et al. 1985). These papers explain how the survey was conducted, outline the work undertaken by two professional agencies, and list the format of computer tapes. Such information is not replicated here; instead the purpose and administration of the Cardiff panel are sketched. Sufficient background material is given to make sure that our study of methodology, description and modelling is meaningful.

1.1 Purposes

Before conducting a social survey it is always necessary to specify the principal objectives. Certainly no amount of checking can correct for ill-defined objectives or an inappropriate structure. Therefore, we need to be aware of what aims were in mind when the project was first proposed.

The initial aims fall into two distinct categories; some refer to specific data requirements, others set forth broad possibilities for future research.

Stipulated above all else was the need for a disaggregate, long-term consumer panel which would be confined to a single urban area. Panel members would keep records of grocery purchases, shop choice and travel. With such data the routine and habitual behaviour of individual consumers could be observed. Because 'normal' behaviour was under observation the panel needed to run for many months in a relatively stable trading environment.

By confining the study to a single urban area it was hoped that patterns of consumer behaviour could be related to the provision of shops, to the ease of travel and accessibility, and to the characteristics of residents. A large sample was needed in order to study a broad range of socio-demographic and housing sub-groups.

Finally, not all types of shopping were to be studied. The focus was on purchases of grocery and convenience goods, and associated travel. Less frequent and less repetitious forms of shopping were not to be considered. No statements were to be made about the consumption of durable and comparison goods or how total family expenditure is allocated.

The second group of aims were broader, and range from methodological and descriptive uses to the application of panel data in models of consumer behaviour.

First of these broader aims was the desire to investigate how consumer panels might be adapted for geographical research. Secondly, the panel data were to provide a comprehensive source for the description of consumer purchasing and human activity. Each purchase occasion was listed separately so that profiles of trips and activities could be re-constructed by researchers at a later date. This approach, however, does not enable the researcher to create complete time-budgets nor study all the activity linkages between members of the family.

Contemporary urban modelling requires micro-scale data, and disaggregate panel records were collected to provide a pool of suitable data. In the original proposals it was envisaged that panel data would be most suited to the development of stochastic models and discrete choice models.

A final ambition was to assist planners, retailers and market researchers in making predictions about consumer behaviour and in assessing changes within the retail sector over recent decades.

In the chapters that follow the influence of these original purposes will become apparent; they make possible (and restrict) the range of issues that can be addressed.

1.2 Administration

The administration of the Cardiff panel spanned several years (for a full account reference should be made to Guy et al. 1983).

In the first instance a pilot survey was completed (September to December 1980). This clarified several important issues and revealed areas of weakness, viz.

(a) the recruitment rate had been over-estimated
(b) the attrition rate was lower than expected

To achieve an adequate response rate and continuing cooperation rates it was discovered that both panellists and fieldworkers needed to be briefed and supervised very carefully. Pilot work also assisted in the wording and layout of forms and in the estimation of costs.

The main survey ran for six months, from February 8 to July 25, 1982. In addition to this 24-week reporting period there was a run-in period of two weeks at the start. It was believed that two weeks would be sufficient for the novelty of being on the panel to wear off. Once the novelty had worn off the behaviour of consumers was unlikely to be conditioned by participation on the panel. In addition,the run-in period enabled response problems to be resolved.

Within the urban area of Cardiff 8 study areas were defined (see section 2.2). After sampling, and after allowing for attrition during the survey, there were 451 panellists who provided a continuous record of their grocery purchases. Over the whole 24-week period these 451 panellists recorded 78,000 shop visits, and spent £265,000 which amounted to about £590 per household.

Two sets of information are available on each panel member, these are the diary records and responses to a couple of questionnaires.

Each page of the diary describes a shop visit (or purchase occasion) and these pages are collected into weekly diaries. Recorded on shop forms are details of:

- the purchase of food and grocery goods, plus cleaning agents, toiletries and preservatives, and amount spent

- the purchase of brands in selected product fields (such as fabric conditioners, baked beans, etc)

- the name, address and description of each shop visited

- travel and activity information, including day,time, form of travel, place come from/going to

Two questionnaires were administered to the person who answered the description: 'responsible for buying most of the groceries and provisions eaten by the household'. The first questionnaire 'broke the ice' between fieldworkers and potential panellists, the principal aim being to recruit people onto the panel. The second questionnaire was more detailed and responses to this questionnaire give details of:

- socio-economic features of panellists (age, education, etc)

- household characteristics (such as length of residence and household size)

- attitudes to shopping

Attitudes were measured using Likert scales. Most questions were general: is it tiring to shop? does shopping get you out of the home? does Cardiff have good quality shops? how important are prices, bargains and freshness? Attitudes about specific shops or centres were not solicited, nor was a study made of consumers' perceptions.

In addition to the information collected from panellists and their households, a complete file of shops visited by the panellists was constructed. For each shop a note was kept of its location, function (baker, butcher, ...) and form of organisation (multiple, independent, ...). These lists were compiled largely from diaries, although during the Summer 1982 a separate survey of shops was mounted. Earlier, in May 1982, a selected prices survey had been completed at 58 shops.

Plainly the administration of the Cardiff panel was a complex, involved and costly exercise and the funding from the Social Science Research Council (ESRC grant D00230010) was crucial to the success of the venture. Crucial too were the professional agencies who collected and managed the data. Research and Marketing (Wales and the West) Ltd was responsible for the day-to-day conduct of the survey and the supervision of fieldworkers. Coding and punching was under the control of DCMS Ltd; this firm also performed consistency checks and validity checks.

2 The Cardiff Study Area

This section outlines the provision of shops in Cardiff and the characteristics of consumers in the study areas. Like section one, most of the material presented here is necessary background information: the retail and social environment is the backcloth on which are played out the details of routine behaviour.

Part one discusses the development of retailing in Cardiff and the influence that planning control has had. The scene is undergoing constant change and several superstores have opened recently. The characteristics of shoppers are discussed briefly in part two; for this purpose use is made of questionnaire data gathered from panellists during the survey. Together, these parts provide an account of the urban structure of Cardiff during the 1970s and 1980s. For an account of earlier periods of growth and development reference ought to be made to Carter and Rowley (1966) and Davies (1983); these authors provide snapshot views of the urban morphology of Cardiff in 1961 and 1971 respectively and are of some historic interest.

2.1 Retailing in Cardiff

Cardiff mirrors, in microcosm, many of the trends that are re-shaping the retail industry. Apart from locational advantages, Cardiff's third of a million inhabitants have enough purchasing power to lure - almost without effort - a large and continuing number of developers and retailers. Because of opportunities for investment the Welsh capital has become fully integrated into the national property scene.

Furthermore, Cardiff and its environs have not been immune from the more specific effects of retail change: hyperstore and supermarket developments, proposals to pedestrianise busy streets and to build covered shopping malls, the spread of fast-food outlets and of retail warehousing for comparison-goods shopping. Change also implies decay, and it is certain that the national loss of 42,700 grocery shops (1971-1979) is reflected in a declining stock of independent retailers in Cardiff.

For the future, many developments will move in tandem with other sectors of the economy. The idea of 'theme centres' implies that the choice of shopping centre may become linked with cultural and leisure pursuits, and this will have an important effect on people's trip-making behaviour. Other developments are tied into the technological and financial sectors - automated stock control and cash control, laser scanning, EFTPOS, home banking and home buying - all these aids to shopping will give rise to new patterns of consumer activity and call for new approaches to marketing.

2.1.1 Planning and Development History

Cardiff has acquired an extensive stock of shops, to the extent that many would suggest over-supply. Even by 1971 Cardiff's 85,000 sq m (net) of retail floorspace compared favourably with 23,000 sq m in neighbouring Swansea and 16,000 sq m in Newport. However, major development was slow after the Second World War and proposals from Buchanan & Partners were not immediately adopted.

Three aspects of what finally has emerged need to be considered. At the regional level central Cardiff's renewal has emphasised specialist, higher-order functions and is seen as serving the needs of South Glamorgan. At an intermediate level are district centres and local centres; these generate intra-urban loyalties and a great deal of localised movement, yet until recently these were poorly researched. Finally, superstores and hypermarkets have prospered in affluent suburban areas; they have generated much research interest and not a little controversy.

(a) Central Cardiff

Higher order functions are concentrated in the city centre. The Census of Distribution (1971) showed that 92% of consumer expenditure in the central area was for durables and it is this image of a higher order regional centre that planners and developers have wished to promote. Yet, convenience retailing is of much importance: in 1971 there were 103 convenience shops located in the central area, not to mention the food-halls of many department stores. Even the Cardiff shoppers of 1982 were able to buy provisions at almost 60 places in the city centre, ranging from department stores to stalls in the open air market.

Comprehensive redevelopment was first envisaged in 1953 and this work culminated in 1973 with ministerial approval of 'Central Area Comprehensive Development Area Number 4 Scheme (1971)'. Plans extended from 73,900 sq m of shopping floorspace, to multi-storey car-parking for 11,000 cars and office space of 18,000 sq m. For such a large scheme Cardiff City Council decided to work in conjunction with Ravenseft Properties, a development subsidiary of Land Securities. By 1975 still nothing had been achieved. Controversy had arisen over social priorities and unsatisfactory financial arrangements - the majority of rental income was projected to benefit Ravenseft Properties, while the costs soared from £47m in 1969 to £126m in 1975 (Hughes 1975, Thomas 1978). The contract was terminated and piecemeal development was allowed.

When the area Structure Plan was produced (County of South Glamorgan 1977a, 1977b), planning emphasis was given to:

- pedestrianisation of the Queen St/Church St/Hayes areas for reasons of consumer safety and convenience

- integration of traffic control with schemes for park'n ride and bus-only lanes

- permission for the development of 42,000 sq m of shopping floorspace

The St David's Centre emerged as the final outcome of comprehensive planning. This centre, developed by Heron, has become the focal point of shopping in Cardiff; it covers 46,460 sq m of floorspace (gross) and includes Marks and Spencer, Debenhams department store, an extended Boots, and 68 smaller units. Adjoining the centre, at The Hayes, is Tesco's superstore (3,300 sq m net), one of 21 new stores that the company opened in 1980/81.

(b) District and Local Centres

The supply of outlets at a local level was deficient in some parts of the city. Cardiff is provided with several thriving district centres, notably Albany Rd and Cowbridge Rd East, yet much of the fabric is aging and perennial problems are raised by access, on-street parking, delivery lorries, and concentrated activity. The total stock of floorspace in district centres represents a considerable social investment, amounting to 39,000 sq m, with 11,000 sq m (29%) devoted to convenience shopping (County of South Glamorgan 1977b).

Located on the map of Cardiff (figure 2.1) are the positions of several district and local centres. The majority are within 2 km of the CBD and several follow main arterial routes. Most important of these is Albany Rd; at the time when the County Council reported its structure plans 2,700 sq m of floorspace was given over to convenience-goods retailing (ie. 24% of all floorspace in this centre).

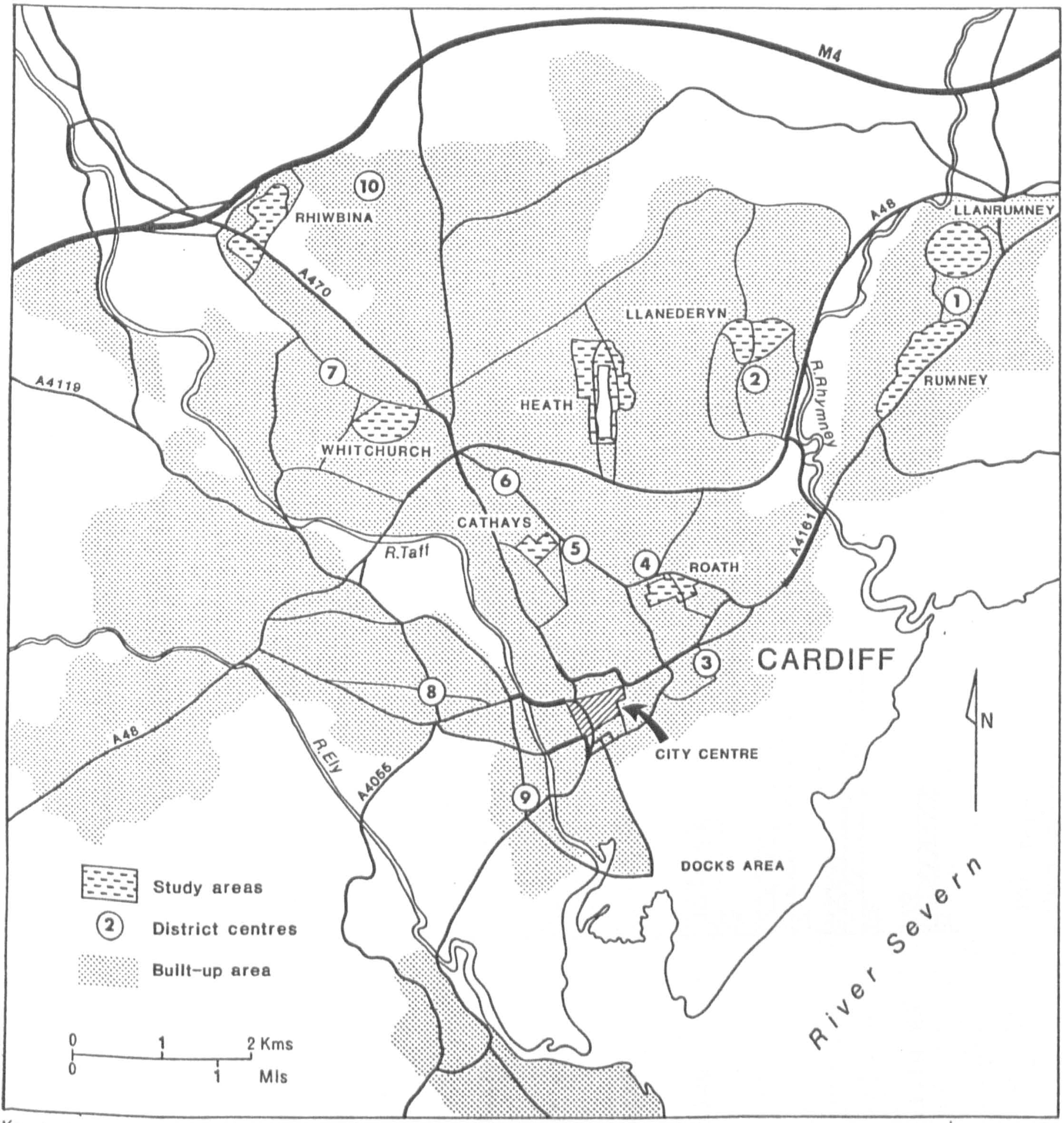
Shoppers in the 1982 panel survey recorded visits to 56 shops in the single district centre at Albany Rd, a figure noticeably higher than any other centre except the central area. Some comparative features are presented in figure 2.2. These features are arranged so that the centre having most floorspace devoted to convenience goods comes first; so Cowbridge Rd East, lying to the west of the River Taff, is followed by Albany Rd, then Llanedeyrn, Merthyr Rd and Clifton St.

This level of the retail hierarchy is most vulnerable to changes in patterns of consumer behaviour: from the switch to bulk-buying, and from the popularity of freezer centres and superstores, and from less frequent rates of trip-making. The planning response has been uncoordinated and cautious, but several themes are evident:

- to reinforce convenience shopping facilities at local and district centres
- to concentrate further shopping development within established nodes of the retail hierarchy
- to restrict large new stores or cash-and-carry warehouses where these might adversely affect existing shops
- to improve the access, servicing and environmental quality of existing centres

Figure 2.1

The City of Cardiff



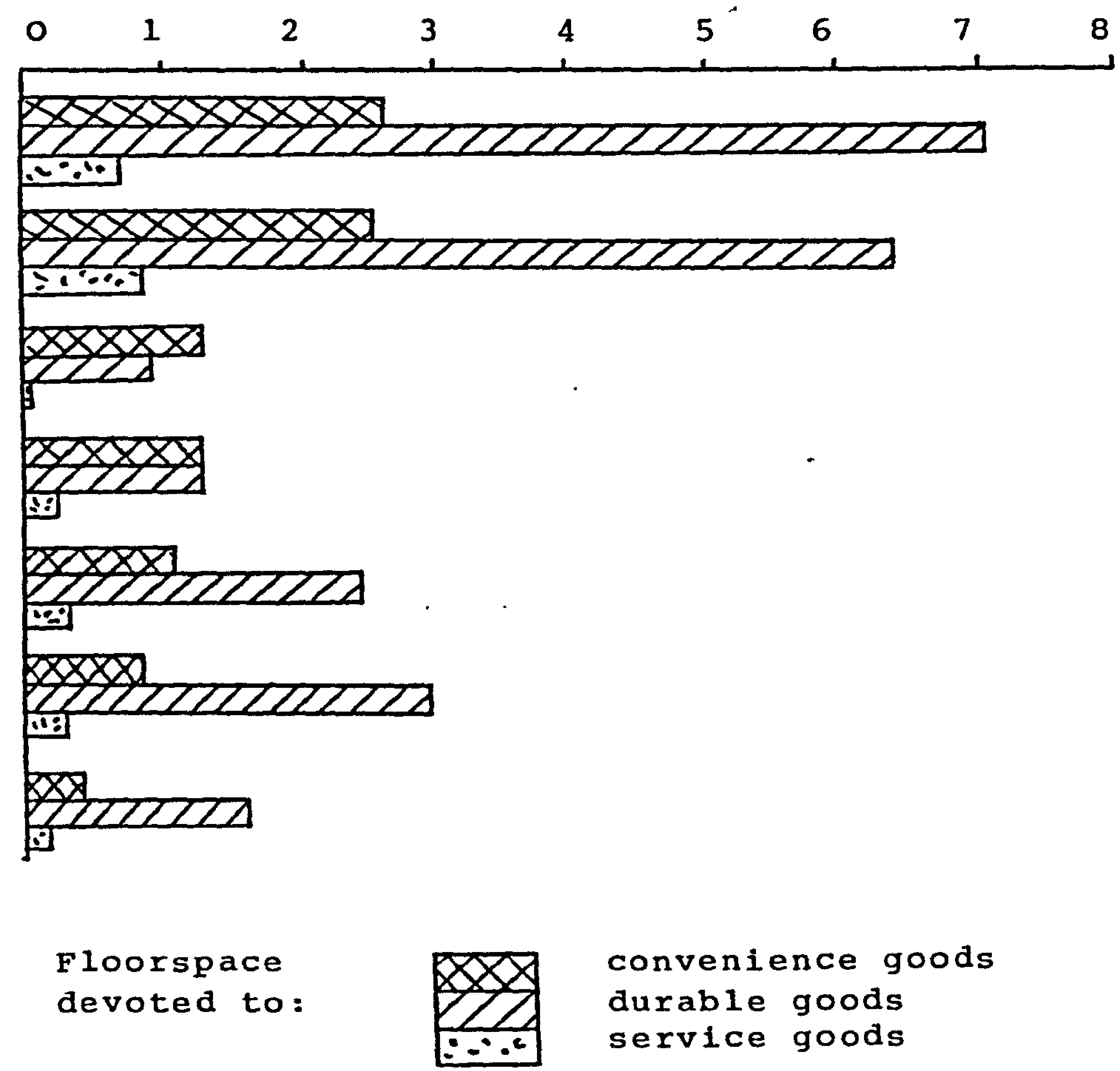
Key to District Centres **1** Countisbury Avenue **2** Maelfa **3** Leo's, Splott **4** Albany Road **5** Crwys Road **6** Whitchurch Road **7** Merthyr Road **8** Cowbridge Road East **9** Clare Road **10** Hoel-y-deri

(Source: Guy et al. 1983)

Figure 2.2

Features of District Shopping Centres in Cardiff

District Shopping Centres	Floorspace Totals ('000 sq m) (source: County of South Glamorgan 1977b)	Number of Shops Visited (Cardiff panel)
Cowbridge Rd East		40
Albany Rd/Wellfield Rd		56
Llanedeyrn/Maelfa		9
Merthyr Rd/Philog		30
Clifton St		28
Whitchurch Rd		24
Crwys Rd/Woodville Rd		37



How far these euphemistic aims are translated into consistent strategies and planning controls is unclear - they may simply fossilise the existing hierarchy.

(c) Superstores and Hypermarkets

By 1982 there were 20 hypermarkets and superstores in Wales, most of them having been the subject of before-and-after impact statements. One main advantage of these outlets is the way that groceries may be purchased in bulk, this form of shopping has particular appeal for the young, middle-income, and mobile elements of the consumer population. Trade areas for such stores are only restricted beyond 16 km (or the 30 minute isochrone), which probably means that Cardiff's retail structure has been affected by several hypermarkets located in Mid-Glamorgan (such as Carrefour at Caerphilly, Leo's at Pyle, and Asda at Dowlais). For example, the Tesco superstore at Talbot Green, Llantrisant, is reported to have drawn 9% of its shoppers from South Glamorgan (including Cardiff).

South Glamorgan itself has been more cautious, preferring to approve superstores rather than full-scale hypermarkets. The position up to the survey period was:

Trading superstore	Opened	Net floorspace sq m (approx)
Leo's, Penarth Rd	1970	1,020
Leo's, Moorland Rd, Splott	1971	3,900
Presto Tower, Barry	1973	2,500
Tesco, The Hayes	1981	3,300
1970 - 81 Total		10,720

Refusals were issued for much larger out-of-town hypermarket proposals from the Autodolen Association (the scheme was to be 8 km east of Cardiff near the M4) and from Woolco (whose proposal was for Penarth, 2.5 km west of Cardiff). In addition to the attractions of superstores, lower- and middle-income mobile shoppers have been drawn to freezer centres and retail warehouses. Many of these have been built on industrial estates and have added an erratic element to the retail hierarchy.

2.1.2 The Current Retail Environment

Convenience goods retailing in Cardiff can be seen as a three-tier arrangement with comprehensive schemes in the city centre, district centres on new housing estates, and proposals for edge-of-town hypermarkets. In view of planning restraints and economic recession the last option is increasingly less plausible and new superstores are more likely to be located within the city boundaries and in association with housing schemes.

(a) Central Cardiff

Slowly retailers are assessing the impact of the St David's Centre. Pedestrian movements have switched noticeably to the new malls off Queen St and away from High St-St Mary St, and in their wake some rents have fallen to a third of prime levels. Other new schemes, however, are awaiting approval: 10,000 sq m of shops near The Hayes (Amalgamated Developers) and 6,000 sq m at the eastern end of Queen St (Sun Alliance) (Estates Times 1983).

The most flamboyant proposal came from Guardian Royal Exchange. Envisaged was a £25m theme centre where 'the whole family could do the shopping as well as take advantage of a wide range of leisure activities and local amenities'. The scheme included provision for one department store, a supermarket, 33 individual shops, and market stalls. City planners opposed the idea during a 5-week public enquiry and in March 1985 the Secretary of State for Wales rejected Guardian Royal's proposal. A revised scheme may now be put forward for the 2.1 ha site.

Refusal of planning permission was not surprising; the complex blatantly went against Structure Plan guidelines and would compete wastefully with other new centres. But, whatever the merits of Guardian Royal's 'Queensgate Centre', the emphasis on a shopping experience is interesting. Convenience retailers, particularly in congested city areas, may have to stress associated activities and attractions (ice-skating rinks, swimming pools, libraries, etc) and be more attune to passing trade from office workers if they are to sustain trading levels.

(b) District Centres and the Outskirts of Cardiff

A couple of new superstores are being used to anchor the large housing developments that are under construction on the outskirts of Cardiff. St Mellons, with 5,000 new houses, has gained a 12,000 sq m (gross) district centre. This includes a 2,700 sq m (net) Tesco superstore, small shops and community facilities. To the north, at Thornhill, another store of similar size has been opened by Sainsbury's; this not only meets the needs of the new community it also answers some of the public disquiet about shopping facilities in the existing suburbs of north Cardiff.

Apart from schemes agreed under the County Structure Plan several other superstores have been opened on appeal sites. These stores include Asda at Coryton in the north-west where floorspace for convenience and durable goods is almost 5,000 sq m, and a combined DIY and superstore development by Sainsbury's at Pen-y-lan.

Projects which have come to fruition since the survey period in 1982 are listed below:

Trading superstores	Opened	Net floorspace sq m (approx)
Tesco, St Mellons	1982	2,700
Sainsbury's, Colchester Ave	1983	2,700
Asda, Coryton	1984	4,700
Sainsbury's, Thornhill	1984	2,300
1982 - 84 Total		12,400

(source: County of South Glamorgan 1984)

Overall, floorspace for grocery and convenience retailing has doubled in the superstore sector since the Cardiff consumer panel was undertaken. The doubling of floorspace means that the total now is 23,000 sq m.

The pace of retail development in Cardiff shows little sign of abating. Tesco has proposals for a 1.5 ha site at Culverhouse Cross. Culverhouse Cross adjoins the M4 and is easily accessible. City planners have opposed the scheme, although the results of an appeal are not expected until 1986.

When these proposed changes to the built environment are combined with innovations inside stores, with expansion of High Street services (from building societies to video shops), and with subtle modifications to consumer activity patterns, then the whole retailing scene looks very fluid. To appreciate the extent of change it is worth re-reading the study by Carter and Rowley (1966); in the past twenty years the pattern of retail provision in Cardiff has changed beyond recognition.

2.2 Characteristics of Consumers in Cardiff

Now attention is turned to the demand side of retailing; ie. the consumers and the types of area from which they originate. Eight study areas lying to the east of the River Taff and north of the city centre were identified during the first phase of sample selection (see figure 2.1 and short descriptions in tables 2.1 and 2.2). These areas were chosen to reflect a range of accessibility and mobility conditions.

The urban morphology of Cardiff is similar to that of many British cities, with sectors of rising affluence interspersed by post-war council estates on the suburban fringe. Within this morphological framework the study areas are grouped into an inner-city residential core, suburban public-housing estates and suburban private-residential estates.

Table 2.1

The Demographic Characteristics of Consumers in Study Areas

Study Areas	Age of panellist (%)							Total
	16-24	25-34	35-44	45-54	55-64	65-74	>74	
Cathays	11	38	14	10	12	14	1	100
Heath	0	26	31	10	23	10	0	100
Llanedeyrn	6	56	22	6	11	0	0	100
Llanrumney	2	23	11	33	20	11	2	100
Rhiwbina	0	15	23	35	19	7	1	100
Roath	15	33	7	7	15	22	0	100
Rumney	2	22	13	20	32	7	5	100
Whitchurch	0	36	25	18	11	9	0	100
Cardiff	4	30	18	20	18	9	1	100

Study Areas	Marital status (%)			Total
	married	single	divorced widowed	
Cathays	73	14	14	100
Heath	90	3	8	100
Llanedeyrn	81	0	19	100
Llanrumney	85	2	14	100
Rhiwbina	88	3	9	100
Roath	59	19	22	100
Rumney	72	3	25	100
Whitchurch	93	0	7	100
Cardiff	81	5	14	100

Table 2.2

The Socio-Economic Characteristics of Consumers in Study Areas:
(a) Length of Residence and Education of Panellists

Study Areas	Length of residence (%)							Total
	<6 months	6-12 months	1-2 years	2-3 years	3-10 years	>10 years	don't know	
Cathays	4	12	7	7	29	41	0	100
Heath	3	10	13	8	21	46	0	100
Llanedeyrn	0	6	13	9	24	46	2	100
Llanrumney	0	3	0	5	20	73	0	100
Rhiwbina	1	3	0	3	25	67	0	100
Roath	4	4	11	19	30	33	0	100
Rumney	0	2	0	8	28	60	2	100
Whitchurch	0	0	7	2	34	55	2	100
Cardiff	1	5	5	7	26	55	1	100

Study Areas	Age at end of full-time Education (%)							Total
	<14	15	16	17-18	>19	still study	don't know	
Cathays	23	23	22	17	10	3	1	100
Heath	5	8	31	20	31	3	3	100
Llanedeyrn	17	50	20	10	4	0	0	100
Llanrumney	44	26	21	9	0	0	0	100
Rhiwbina	9	16	32	24	17	0	2	100
Roath	26	22	19	4	19	11	0	100
Rumney	43	35	12	2	2	0	7	100
Whitchurch	18	20	18	7	9	0	27	100
Cardiff	24	25	22	13	10	1	4	100

Table 2.2 (cont.)

The Socio-Economic Characteristics of Consumers in Study Areas:
(b) Freezer Ownership and Work Status of Panellists

Study Areas	Whether a separate freezer is owned (%)		
	yes	no	total
Cathays	41	59	100
Heath	59	41	100
Llanedeyrn	43	56	100
Llanrumney	39	59	100
Rhiwbina	57	43	100
Roath	26	74	100
Rumney	33	67	100
Whitchurch	57	43	100
Cathays	45	54	100

Study Areas	Work status of panellists (%)			
	full-time job	part-time job (+student)	retired not working	total
Cathays	21	32	48	100
Heath	21	31	49	100
Llanedeyrn	11	31	57	100
Llanrumney	15	29	56	100
Rhiwbina	23	34	43	100
Roath	11	11	78	100
Rumney	8	32	60	100
Whitchurch	5	30	66	100
Cardiff	15	30	55	100

Table 2.2 (cont.)

The Socio-Economic Characteristics of Consumers in Study Areas:
(c) Occupation of Panellists

Occupation of Panellists (%)	Cathays	Heath	Llanedeyrn	Llanrumney	Rhiwbina	Roath	Rumney	Whitchurch	Cardiff
professional	4	3	0	0	5	0	0	0	2
intermediate non-manual	15	23	7	5	18	11	5	2	11
junior non-manual	21	13	13	18	33	4	8	14	18
personal service	3	3	4	5	3	4	7	5	4
foreman/ supervisor	0	0	0	2	0	0	3	0	1
skilled manual	1	0	2	2	0	0	2	0	1
semi-skilled manual	3	0	0	2	1	0	2	0	1
unskilled manual	5	5	15	14	0	0	8	2	6
own account	0	0	4	0	0	0	2	0	1
armed forces	0	0	0	0	0	0	2	0	0
not working	44	51	56	55	40	74	57	64	52
student	3	0	0	0	0	7	2	0	1
no answer	1	3	0	0	0	0	3	14	2
total	100	100	100	100	100	100	100	100	100

(a) Inner city

Roath and Cathays are model inner city areas.

Roath lies nearest to the old industrial zone and docklands, and during the 1970s its population was in decline. A transient population occupies the aging fabric, much of which is subdivided and let as private flats and bedsitters. Family incomes are low and many workers have manual and semi-skilled occupations. The residents of this area are close to good shopping facilities and the city centre is very accessible.

The age distribution of panellists who live in Roath is bimodal. Some 15% are aged 16-24 years and 22% are aged 65-74 years; these high proportions compare with Cardiff averages of 4% and 9% in each age group respectively (table 2.1). Much of the population of Roath is mobile, and of panellists 38% have lived there for no more than 3 years (table 2.2 (a)). Most panellists are women who are generally without paid jobs. A high proportion, 22%, are separated or widowed and a further 19% are single.

Cathays is a distinctly residential inner-city district. Until the 1970s the residential core was aging and houses lacked basic amenities, since then renovation has improved the quality of property. Young families, many of whom are immigrants, live here. Central shopping facilities are no more than 1.3 km away, and the shops at Crwys Rd and Albany Rd are nearby.

The demographic and socio-economic characteristics of panellists are similar to those for people living in Roath. There is a bimodal age distribution, the number of single persons is above the Cardiff average, and about 16% of panellists have not been living in the area for more than one year. Because of proximity to UWIST and several University Colleges many students live in these areas, and a couple participated on the panel.

(b) Suburban public housing

Collected under this heading are the areas of Rumney, Llanrumney and Llanedeyrn.

Housing in Rumney comprises pre-war and 1970s council estates. The population is steady and still fairly young. Local shopping facilities are limited, although the precinct at Countisbury Avenue serves as a district centre (de facto).

Amongst panel members there is an exceptionally large number of divorcees and widows (25%). Most panellists are women, and merely 8% hold full-time jobs. Of those panellists who have a job (part-time or full-time), those living in Rumney are least well represented among intermediate and junior non-manual occupations (table 2.2 (c)). The occupational structure reflects local opportunities (or lack of them) and educational background - 78% of panellists in Rumney left full-time education before they were 16 years old.

Llanrumney consists of a large council estate on which are living low-income and low-mobility groups of people. Few households have an inflow of two incomes and social worker case-loads are high. Shops are poor and many consumers are reliant on public transport.

Many panellists who live in Llanrumney are aged 45-64 years (this group represents 53% of panellists), and 73% of these have lived in the area for more than 10 years. Almost three-quarters of these people finished their full-time education before they were 16 and about 14% now have unskilled manual occupations (ie. cleaning, catering and shop work). Most household heads have manual occupations: in Llanrumney 62% of household heads are in manual occupations, which contrasts with less than 6% in Heath and Rhiwbina.

Llanedeyrn grew up during the 1960s and now has large council and private estates. Mainly young families live here. The district shopping centre is part of the estate (Maelfa precinct) and most panellists do not find difficulty in reaching these convenient facilities.

Llanedeyrn is dominated by people aged 25-34 years; 56% of panellists are in this age group. In terms of marital status, length of residence, work status and freezer ownership the panellists from Llanedeyrn approximate the average situation for the Cardiff panel. An unusually large number of women who work are doing unskilled manual tasks, such as cleaning and catering.

(c) Suburban private residential

Heath, Whitchurch and Rhiwbina are moderately high-income private-residential areas.

Half the panellists from Heath have lived in the area for more than 10 years, but there has always been considerable mobility and 13% of panel members had moved in within the previous year. Ownership of a separate freezer is greatest in Heath (there is a 59% ownership rate, compared with a 26% rate in Roath), this suggests a high level of affluence. These people have undertaken the greatest amount of formal education; only 5% finished full-time studies before 15 years and 31% continued beyond their nineteenth birthday. Compare these percentages with those for the whole Cardiff panel - 24% and 10% respectively.

Whitchurch, a commuter area built after 1930, has a bimodal population of very young families with children and the retired. This age distribution may account for a full-time employment rate of only 5% among panellists (mostly women). There is good access to the city centre, but local facilities in both Heath and Whitchurch are poor.

Most peripheral of the areas, Rhiwbina lies 6.6 km from the city centre and 2.3 km from Merthyr Rd district centre. Affluence is comparatively high and 24% of the panellists have a combined household income of £10-15 thousand in 1982 (this is double the average recorded for Llanedeyrn). The majority of families (67%) have lived in the area for more than 10 years.

Local employment opportunities are good for full-time workers, especially in pharmaceuticals and electronics, also in teaching and professional occupations. In Rhiwbina over 41% of household heads are professionals, employers or managers, whereas virtually no household heads in Llanedeyrn, Llanrumney and Rumney are represented among these occupations. Disparities also exist between individual panellists (most of whom are women), although none are employers or managers and very few are professionals. Some 51% of panellists in Rhiwbina, and 36% in Heath, hold intermediate and junior non-manual jobs (ie. administrative, clerical and secretarial jobs) whereas very few panellists from these areas hold unskilled/manual jobs. Over 20% of panel members in Rhiwbina have full-time jobs and this area has the lowest proportion of women without work. Consumers living in two-income households can afford to look for quality foods in chain stores and supermarkets, though they are more likely to regard shopping as a time-consuming chore.

As shown by these vignettes, the Cardiff consumer panel includes a wide range of consumer groups. The profile of shoppers, however, is not complete. Wealthy consumers living in the Vale of Glamorgan are excluded yet they take full advantage of facilities within the city boundary. At the opposite end of the social scale, truly working-class inner-city residents (living in Riverside, Adamstown and Grangetown) are excluded too. Moreover, it is probable that the city's substantial foreign-born communities are not well represented.

3 Methodology of the Cardiff Consumer Panel

Many sophisticated models are estimated from fairly unsophisticated data. Records are incomplete, sample biases exist, respondents often misunderstand what they have to do, records might be coded incorrectly - all these sources of error give rise to imperfect social survey data. Even where the collection of data is carefully controlled, the method of control influences the findings that are ultimately obtained.

Attention to the method of collection and the quality of data should give us confidence for the descriptive and modelling exercises that follow. Occasionally awareness of shortcomings in the data makes it possible to take corrective action, such as re-weighting responses to provide a more representative sample. More likely, however, the researcher has to live with the data and methodology is studied to add a note of caution. At the very least these studies serve as a warning and guide researchers who wish to perform similar exercises in the future.

Social scientists have given much attention to questions of sampling error and sample representativeness. These questions arise every time a standard cross-sectional questionnaire is administered. Because discussion of these topics is so readily accessible to a geographical audience our treatment of them is cursory. Longitudinal data, on the other hand, introduce many unfamiliar sources of error. In longitudinal studies initial response rates tend to be poor, bias may arise from panel attrition, some people alter their behaviour when they participate on the panel, and so on. A few important problems are listed in figure 3.1.

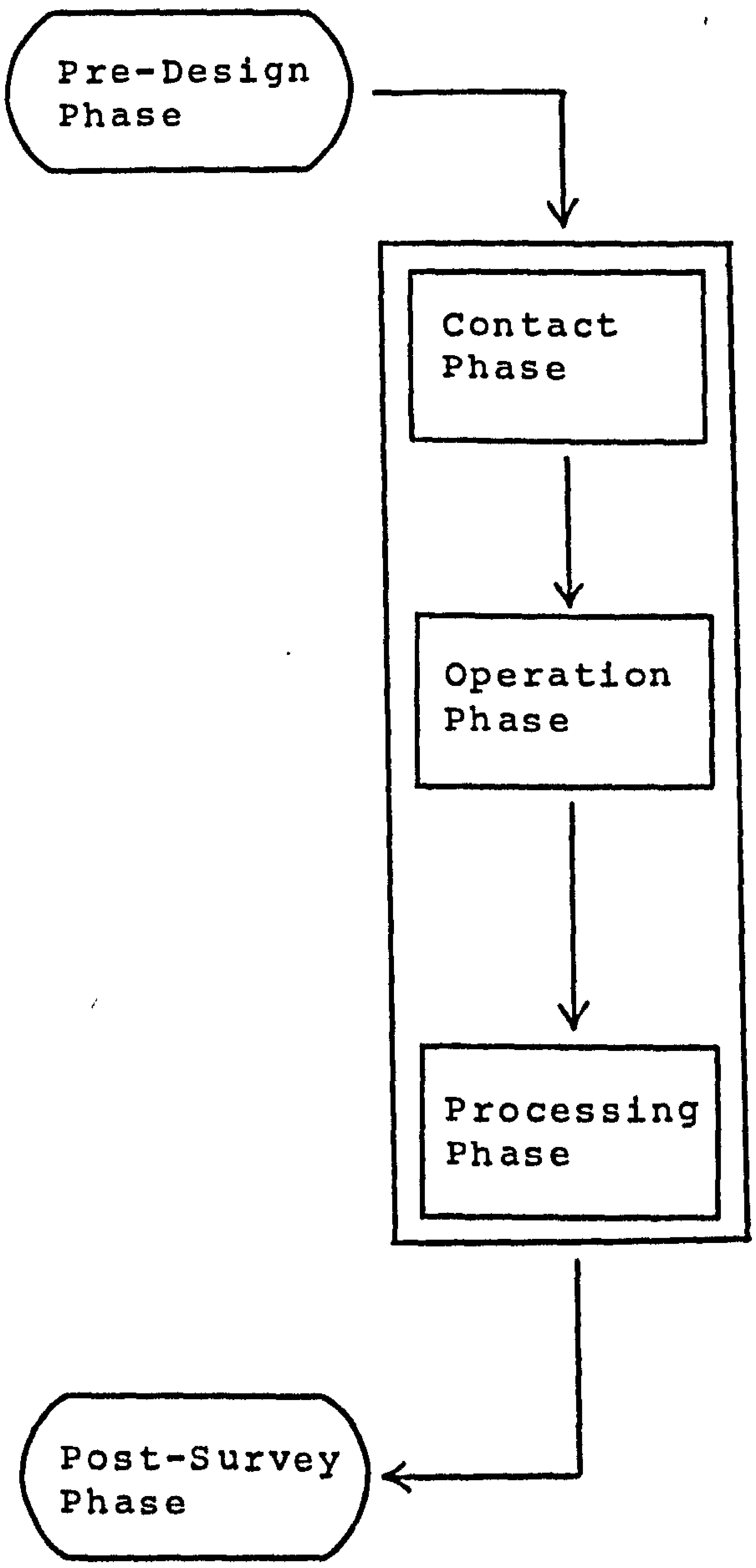
Imprecise definition of purpose is a problem that belongs to the pre-design phase and has been considered in section 1.1. Stratification bias is a conventional problem in all social surveys, we simply note that Cardiff was divided into 8 non-contiguous study areas and within each of these a stratified random sample was selected. An alternative procedure would have been to use quota sampling.

Often there are serious difficulties in recruiting people onto a consumer panel (section 3.1), and keeping them for a lengthy survey period (section 3.2). Once the panel is in operation misleading information might be given. Sometimes personal behaviour is altered because of being on the panel ('conditioning'). On other occasions incomplete records are returned or diary completion is affected by the layout of entries on each page ('systematic ordering effects'). These issues are discussed in section 3.3.

The temporal dimension is crucial in the analysis of panel data, so it is necessary to check the relationship between methodology, stability and repetition. Perhaps panellists become less enthusiastic as time progresses and as a result their records are error-prone. Surprisingly little work has been done to investigate the possibility that record-keeping systematically

Figure 3.1

Sources of Bias and Imprecision during the Operation of a Consumer Panel



Imprecise definition of purpose

Stratification bias

Panel recruitment bias

Conditioning

Attrition

Diary layout and incomplete records

Systematic temporal effects

Editing and coding errors

Imprecise interpretation of terms

deteriorates. Two detailed studies are presented here (sections 3.4 and 3.5). It will be seen that there are difficulties in separating real seasonal effects from spurious recording errors.

Finally, the imprecise interpretation of terms is mentioned. This is a post-design issue, yet one that depends upon decisions made during the design phase. An important distinction, for instance, has to be drawn between the records kept by individuals to describe their own movements and records kept by all members of a household to describe all their movements.

3.1 Bias during Panel Recruitment

During the first stage of fieldwork the market research company administered an initial questionnaire. Answers to the final question stated whether the respondent was willing to complete a shopping diary each week. Some 605 respondents agreed to keep shopping diaries ('panellists') and 632 declined ('non-panellists').

The 605 respondents recruited onto the panel represent 30% of households selected under the original sampling scheme or 49% of households actually contacted and interviewed. Whichever percent is considered the recruitment rate meets the target levels established by the pilot survey.

Snowfalls during the recruitment phase probably discouraged some respondents from joining the panel. Respondents were asked to participate for an unusually long duration, this must also have discouraged many potential panel members. This reason might explain why recuitment in Cardiff was marginally below rates that have been reported elsewhere; for example the 4-week survey at Bretton obtained a 59% success rate (Rogers 1974) and 63% of the potential sample was recruited onto the Watford panel (Daws and McCulloch 1974). As a rule, a shorter panel is able to command the support of relatively more initial contacts.

From the socio-demographic data collected in the initial questionnaire it is possible to compare panellists with non-panellists and to assess the degree of sample bias. Several formal tests are available to compare the two groups (t-tests and χ^2 tests). Formal tests have been calculated but in many cases sample sizes are too small to give reliable results and sometimes 'rules of thumb' have been used.

Over the next few paragraphs the major discrepancies are summarised, however the overriding conclusion is that panellists and non-panellists are reasonably alike. In general, the biases that exist will not alter our interpretation of consumer behaviour in Cardiff.

General discrepancies are described first, then a number of specific effects are noted.

Personal characteristics:

- those shoppers who have access to at least one car show a greater willingness to join the panel
- principal food purchasers are generally women; and,of these,part-time workers are more cooperative
- it proved easier to recruit women aged 25-34 than to recruit persons aged 65 years or more

Household characteristics:

- households with members 5-44 years old are easier to recruit than elderly households
- single persons are hard to attract onto the panel
- despite the extra workload in families with children ('young nuclear families'), these types of household are more willing to participate on the panel

To a large extent many of the biases that arise during panel recuitment re-emphasise the sampling biases of the initial sampling scheme. This is especially true of the tendency to attract young women who are without a full-time job and yet who are mobile.

The sample biases reported here are remarkably similar to those listed by Sudman and Ferber (1979) for household panels in the USA. These authors found that panel recruitment was easiest in households of two or more members and where shoppers were young or middle-aged. Least cooperative were single-member households and the elderly, either because of contact difficulties, disinterest in 'homemaking', or lower educational standards. Similarly, in a British study of store impact, the panel that was finally recruited over-represented 4-person households and those with young children (Rogers 1974).

3.2 Bias from Attrition

All consumer panels are dynamic: people move home; others are affected by bereavement, illness and death; the size of households expands and contracts. Natural causes of panel mortality - the loss of panel members - are compounded by lethargy and boredom amongst members and this necessitates their removal. Throughout the life of a consumer panel losses occur, what we need to establish is how this steady attrition affects the quality of our data.

Summarised first is the overall pattern of attrition, then the characteristics of 'stayers' and 'dropouts' are compared using data from the initial questionnaire.

The overall pattern of attrition is depicted in table 3.1. Over 2000 households were selected initially, of these 61% were actually contacted and 605 respondents agreed to join the panel. Recruitment, therefore, had a success rate of 30%. The panel itself operated for 26 weeks, the first two weeks being treated as a run-in period during which panellists became familiar with what they had to do. Most of the problems associated with attrition and conditioning are concentrated into these first two weeks; 77 panellists had left before week 1 of the main observation period. A further 47 panellists left over the next 24 weeks. In other words, 62% of the loss over 24 weeks was concentrated into the initial two week run-in period.

Not all people who completed diaries for 24 weeks have been retained in subsequent analyses. Some have been removed because they gave imperfect records (there were long gaps or incomplete forms) while others refused to answer a second questionnaire that sought essential socio-demographic and attitudinal information. The final working sample comprises 451 panellists, 25% fewer than the number who had originally agreed to join the panel.

When compared against other consumer panels operated in Britain and the USA the recruitment rate is fairly poor, but this is compensated by a much better (ie. lower) attrition rate. The continuing cooperation rate of 75-80% is significantly above the norm of about 50%. Rapid attrition early on, followed by a gradual levelling off, is the common pattern found in all consumer panels. Moser and Kalton (1972), for example, quote the case of Attwood's consumer panel for non-durable goods: in the first instance 80% of contacts agreed to join the panel, yet by the first reporting period 20% had dropped out and a further 16% left during the next few weeks. By week 6 only 48% of the original contacts remained.

Table 3.1 (a)

Size of the Cardiff Consumer Panel:
Recruitment, Attrition and Loss

Study Areas	Initial Questionnaire		Number who agreed to join panel	Panellists remaining after run-in period (week 1)	Panellists remaining at end of survey (week 24)	Final Questionnaire	
	Households selected	Successful contacts				Number retained for study	Number retained when income is studied
	col 1	col 2	col 3	col 4	col 5	col 6	col 7
Total	2012	1237	605	528	481	451	303
Rhiwbina	225	162	104	98	97	88	50
Whitchurch	292	143	77	66	52	44	25
Cathays	225	163	82	78	77	73	43
Roath	316	154	36	33	28	27	24
Rumney	257	150	75	63	61	60	35
Llanrumney	225	180	102	77	68	66	49
Llanedeyrn	225	132	73	64	56	54	46
Heath	247	153	56	49	42	39	31

Table 3.1 (b)

Size of the Cardiff Consumer Panel:
Recruitment, Attrition and Loss

Study Areas	Success rate %	Attrition rate %	Loss rate %
Total	30	20	25
Rhiwbina	46	7	15
Whitchurch	26	32	43
Cathays	36	6	11
Roath	11	22	25
Rumney	29	19	20
Llanrumney	45	33	35
Llanedeyrn	32	23	26
Heath	23	25	30

Success rate: percent of households selected (col 1) who agree to join the panel (col 3)

Attrition rate: percent of those who agree to join the panel (col 3) but fail to complete the survey (col 5)

Loss rate: percent of those who agree to join the panel (col 3) but are not retained for analysis (col 6)

(Column numbers refer to part (a) of table 3.1)

Patterns of attrition are disaggregated for the 8 study areas in the second section of table 3.1. Attrition and loss rates are severe in Whitchurch and Llanrumney; in particular a disproportionately large number of elderly persons are lost. Taken collectively, the study areas reveal two contrasting processes:

(a) It is very difficult to recruit people in inner city areas, but once these people have been recruited their attrition rate is about average. Thus, out of 316 households selected in Roath only 36 were recruited onto the panel, yet 78% of these completed diaries for the full 24 weeks.

(b) It is easier to inveigle initial support from people who live in suburban areas, but harder to keep them. In Whitchurch the recruitment rate of 26% is not far below the Cardiff average, yet by week 24 some 25 of those who agreed to join the panel had left to give an attrition rate of 32%.

The penalty of over-zealous recruitment is serious loss at a future date.

Comparison of those who remain on the panel ('stayers') and those who leave ('dropouts') shows that in general the two groups of people are much alike. Those who leave are fairly typical of those who stay. Where differences do emerge they tend to be minor and reinforce existing biases. Thus, older members (over 45 years) and those without access to a car are more likely to drop out. No significant differences are detected with regard to household size, employment or sex.

A further division is made to separate early, middle and late dropouts. Thus, during the early phase (weeks 1 to 2) almost 80% of those leaving the panel are over 45 years and about 60% live in households which do not contain a vehicle. Such a concentration among the immobile elderly is not repeated in the middle and late stages, and up to 30% of late dropouts are in the 25-34 age group. Sample sizes are low in these latter stages and not too much reliance should be placed on the conclusions.

The reason for the loss of panel members is documented in several instances. In a few cases consumers are removed because they prove to be unreliable and become tired, at least four were hospitalised and four left the area. Other reasons were long periods away from home, family bereavement and family separation.

The conclusion that attrition bias is not severe and only likely to reinforce existing sample biases is wholly consistent with findings reported elsewhere (Sobol 1959, Sudman and Ferber 1979). Many aspects of attrition bias are irresolvable, but a number of procedures can be adopted in order to maintain a panel:

- take account of problems encountered during the pilot survey

- initial contact should be face-to-face and, during regular visits, fieldworkers should be encouraged to establish a rapport with panel members

- carefully train both fieldworkers and panellists (ie. everyone should know what is expected)

- an adjustment period of at least two weeks should be used to screen out potentially unreliable panellists

- compensate people who keep diaries (Cardiff shoppers received up to £25 if they completed the whole survey, this required an outlay of £10,000).

Apart from preventative measures there are a number of corrections that can be applied. First, as new households are formed (through marriage and in-migration) a proportion are recruited onto the panel. Dynamic replacement of this type helps to retain a representative panel. Second, a 'correctly' composed panel is obtained by applying weights ('post-stratification'). Weighting produces a sample that is representative of census data, which does not mean that it is representative of behaviour or attitudes. The propriety of weighting is open to doubt but the practice is standard in AGB Research Ltd and was done when they administered the Watford travel survey.

3.3 Diary Layout

Diary methods make heavy demands on members of the panel and it is important that sources of error which arise from the workload are kept to a minimum. The ease with which tasks are completed may be improved if attention is given to diary layout, question flow, wording and phraseology and the compactness of diary sheets.

Many comments regarding the layout, wording and presentation of standard questionnaires are relevant (Moser and Kalton 1972, Dixon and Leach 1979, Belson 1981). Belson, in particular, shows how measurement of readership levels is affected quite dramatically by the wording and order of items on the printed page. These effects become that much more important in panel designs where a greater degree of commitment is expected and where panel fatigue can become an acute problem.

Diary sheets in the Cardiff panel were A4 size and collected together into weekly booklets. On each page there were a number of pre-categorised entries which panellists were expected to circle after each purchase occasion. These entries covered topics such as day, time, who made the purchase and form of travel. Because entries were arranged along categorical scales, diary sheets proved simple to complete, code and store. Yet even with this straight-forward layout some records are incomplete, this is most true of questions about activities pursued before and after shop visits.

Apart from shopping activity and travel data, detailed information was sought regarding shop location, expenditure, products bought and brands chosen. A product list or ledger was used to elicit purchase data (figure 3.2). Each panellist ticked the product field(s) which corresponded to the purchase(s) made. Any difficulties could be discussed with fieldworkers or by reference to a checklist of products.

Product lists usually work well, although sometimes there is a tendency to gain greater accuracy where items head a list or where they have prominence on the printed page. The effect is termed 'systematic ordering' and may be tested by arranging product fields into two alternative sequences. Two sequences (white and yellow) were used for the Cardiff diaries:

white forms: products 01-20, 21-39, 40-67
yellow forms: products 01-20, 40-67, 21-39

These forms were distributed among members of the panel in each area. Once completed a check was made to see whether there were significant differences between white and yellow forms.

Some comparisons are illustrated in table 3.2. Only 6 product fields are shown and the mean rates refer to purchases over 4 weeks in Rhiwbina. All t-tests are low, and even if the significance level is dropped to 90% only one discrepancy between mean values is observed (ie. margarine in week 2). Such observations are widespread, and we can state that there is no evidence of systematic ordering effects in the Cardiff data.

If diaries are to be completed accurately and consistently the layout should be kept simple and factual. That way panellists become thoroughly familiar with the entries and they complete their forms automatically. Moreover, when forms are filled in routinely and without deliberation the problem of conditioning is less likely to arise.

3.4 Analysis of Stability

It is important that panellists complete their diaries precisely so that the final record of events is consistent through time. Yet there is a real danger that once the novelty of participation on the panel has worn off respondents become lax and imprecise. Thus, quite apart from the biases that arise when people are lost from the panel (attrition), there is a need to consider how judiciously panellists maintain their diaries.

Recording bias arises from three sources: memory fallibility, invention and vagueness. When there is a failure to record events that actually occur the most likely reason is that people's memories are fallible. Invention is the spurious recording of events that are irrelevant to the study, such as the inclusion of non-grocery trips in a survey of grocery buying. Vagueness is typified by the miscoding of details which describe an event; sometimes, for instance, the amount spent on goods is recorded inaccurately. All these recording problems will

Figure 3.2

The Layout of a Diary Sheet

FOR OFFICE USE

Resp. No.

Week/day No.

Shop No.

Date

NO LISTED ITEMS BOUGHT THIS DAY

DAY OF WEEK

Monday	1
Tuesday	2
Wednesday	3
Thursday	4
Friday	5
Saturday	6
Sunday	7

PERSON BUYING

Panellist	1
Other Household Member	2
Non-Household Member	3

TIME OF PURCHASE

Before 10 a.m.	1
10 - 12 Noon	2
12 - 2 p.m.	3
2 - 4 p.m.	4
4 - 6 p.m.	5
After 6 p.m.	6

MAIN FORM OF TRAVEL TO THIS SHOP/SUPPLIER

No travel	1
Walked	2
Bus/Coach	3
Car	4
Train	5
Other (specify)	6

PRODUCTS PURCHASED (MARK WITH X BELOW)

01	* Fabric conditioners *	01
02	Washing-up liquid	02
03	Household soaps/cleansers/polishes	03
04	Washing powders/detergents	04
05	Kitchen foil/cling film	05
06	Matches	06
07	Paper kitchen towels/tissues/handkerchiefs	07
08	Disinfectants	08
09	* Toilet rolls/paper *	09
10	Bread, rolls, buns, scones, crumpets, etc.	10
11	Biscuits, crispbreads (any type)	11
12	Cakes and pastries (fresh/packaged/frozen)	12
13	Savoury snacks, crisps	13
14	Plain flour	14
15	Self-raising flour, cornflour	15
16	Sugar (any type)	16
17	Marmalade	17
18	Jams, sweet spreads (other than honey/syrup)	18
19	Honey, syrups, treacles	19
20	Pastes, savoury/cheese spreads, pate	20
21	* Canned baked beans (with tomato sauce only) *	21
22	Canned milk puddings	22
23	Other canned desserts, canned custard	23
24	Mixes (cake/pudding/pastry/dessert), custard powder	24
25	Ice cream, frozen desserts, chilled desserts, etc.	25
26	Jellies	26
27	Canned soups (any type)	27
28	Dried/packet/cube soups	28
29	Rice, pasta products (not canned milk puddings)	29
30	Breakfast cereals (any type)	30
31	* Instant potato *	31
32	Other dried vegetables	32
33	Fresh vegetables	33
34	Frozen vegetables	34
35	Canned/bottled vegetables	35
36	Fresh fruit	36
37	Frozen fruit	37
38	Canned/bottled fruit	38
39	Dried fruits, nuts, fruit and nut products	39
40	* Margarine *	40
41	Butter	41
42	Fresh liquid milk (including Long Life)	42
43	Cream, yogurt, canned milk, milk powders	43
44	Cheese (any type)	44
45	Cooking fats, lard, suet	45
46	Cooking oil	46
47	Eggs	47
48	Fresh meat, poultry	48
49	Frozen meat, poultry	49
50	Bacon, ham (uncooked)	50
51	Sausages, meat pies, cooked meats, beefburgers	51
52	Canned meat/ham/other meat products	52
53	Fresh fish	53
54	Frozen fish/fish products (not fish fingers)	54
55	Fish fingers	55
56	Canned/bottled/smoked fish	56
57	* Instant coffee *	57
58	Ground, bottled coffee	58
59	Cocoa	59
60	Drinking chocolate, Ovaltine, Horlicks, Bournvita	60
61	Tea (packet/bags/instant)	61
62	Soft drinks, squashes, cordials (canned/bottled)	62
63	Fruit juices (any pack)	63
64	Sauces, pickles, salt, vinegar, stuffings, etc.	64
65	Meat/veg. extracts, stock cubes, spices, herbs	65
66	Baby food products (any type)	66
67	Confectionery (chocolates and sweets)	67
68	Other foods not listed (please specify below)	68

CAME TO THIS SHOP/SUPPLIER FROM (PLACE)

Supplier called	1
Home	2
Workplace	3
Shop where listed items bought	4
Shop where other items bought	5
Other place (specify)	6

WENT FROM THIS SHOP/SUPPLIER TO (PLACE)

Supplier called	1
Home	2
Workplace	3
Shop where listed items bought	4
Shop where other items bought	5
Other place (specify)	6

SHOP/SUPPLIER

Name ....

Street ....

District ....

Town ....

* MAKE/BRAND BOUGHT OF SELECTED ITEMS *

FABRIC CONDITIONERS

Comfort	1
Lenor	2
Softlan	3
Spar own brand	4
Other (specify)	5

TOILET ROLLS/PAPER

Andrex	1
Co-op own brand	2
Delsey	3
Dixcel	4
Izal	5
Kleenex	6
Other (specify)	7

BAKED BEANS

Chef	1
Crosse & Blackwell	2
Heinz	3
H.P.	4
Tesco own brand	5
Other (specify)	6

INSTANT POTATO

Co-op own brand	1
Smash	2
Wondermash	3
Yeoman	4
Other (specify)	5

MARGARINE

Blue Band	1
Echo	2
Flora	3
Krona	4
Stork	5
Stork S.B.	6
Tesco own brand	7
Other (specify)	8

INSTANT COFFEE

Brooke Bond - Red Mountain	1
Co-op own brand	2
Maxwell House	3
Mellow Birds	4
Nescafé - Gold Blend	5
Nescafé - Standard	6
Other (specify)	7

	£	p
TOTAL AMOUNT SPENT ON LISTED ITEMS		
TOTAL AMOUNT SPENT ON OTHER ITEMS		
TOTAL AMOUNT SPENT ON ALL ITEMS		

Table 3.2

Systematic Ordering Effects:
Comparison of White and Yellow Forms, Week 1 to Week 4

Products bought:	fabric conditioner	toilet rolls	margarine	instant coffee	canned baked beans	instant potato
Rhiwbina	Mean Number of Products Bought by Panellists					
Week 1						
W	0.01	0.70	2.51	2.73	1.47	0.23
Y	0.01	0.70	2.81	2.00	1.08	0.36
t-value	1.00	0.02	0.70	0.85	1.03	0.56
Week 2						
W	0.02	0.58	1.91	3.11	1.08	0.21
Y	0.01	0.66	3.24	1.96	1.39	0.08
t-value	0.53	0.45	1.74	1.30	0.83	0.87
Week 3						
W	0.01	0.62	2.46	3.30	1.22	0.22
Y	0.01	0.77	3.30	3.13	1.15	0.16
t-value	0.66	0.77	1.02	0.16	0.16	0.37
Week 4						
W	0.01	0.54	3.22	2.10	1.41	0.10
Y	0.01	0.69	2.69	1.64	1.11	0.15
t-value	0.68	0.84	0.68	0.61	0.80	0.29

W mean of white forms
Y mean of yellow forms

95% significance level 1.96

multiply if members of the panel suffer from fatigue.

While recording biases are easy to define, any attempt to isolate them has to contend with the practical difficulty that errors are not easily disentangled from real trends in the longitudinal record. Systematic recording biases and seasonal rhythms are not readily separated.

Below, an attempt is made to analyse stability. First we see if there are any long-run trends in the data. If there are trends we ascribe them to recording bias or seasonal factors. Several measures of consumer behaviour are selected for the analysis of stability (for example shop visits, trips, and expenditure). These measures are not formalised until chapter 2 and for the present we need only note that they are important summaries of activity.

Average figures are calculated each week for 24 weeks, and then for the whole panel measures of dispersion are obtained (table 3.3). The 'typical' consumer undertakes 6.4 shop visits per week, though for any one week this number might vary by .43 visits. Shopping trips number about 4.5 per person per week with a variation of almost 0.3 either side of the mean. Expenditure on listed goods amounts to £23 on average per week, and the standard deviation is £1.20.

Also listed in table 3.3 are some measures for each day of the week. It is the dispersion around mean values that is of interest, not the daily means themselves. Variation is slight. Mondays - with standard deviations double those recorded on other days - reveal an exceptional degree of variation. Apart from Sunday, Monday is the least important day for grocery shopping and yet it exhibits the largest amount of variation. A plot of how mean values vary throughout the 24 weeks helps to explain this exception.

Weekly mean values are converted into standard normal deviates (z-scores) and plotted in figure 3.3. Section (a) shows a slight decline in mean values for grocery shop visits; up to about week 8 z-scores are definitely above the mean, whereas after week 19 z-scores fall below the mean. In absolute terms there are 6.9 shop visits in week one and 6.4 in the final week. While recording accuracy does undergo a decline it must be acknowledged that the trend is undramatic. Turning to part (b), a steady decline is observed on some days, but this is neither consistent nor convincing. The pattern of mean values for Monday is erratic and particularly unusual in weeks 10, 13 and 17.

Two factors underlie these findings. First, the shallow decline in shop visits (in aggregate) arises from panel fatigue. That consumers tire of completing their diaries is hardly surprising, and it is to their credit that the decline in recording rates is barely detectable. There are several reasons why fatigue is less severe than one might expect:

- panellists were screened and briefed during the two week adjustment period

Table 3.3

Analysis of Stability: Absolute Means and Measures of Dispersion for aspects of grocery shopping over 24 weeks

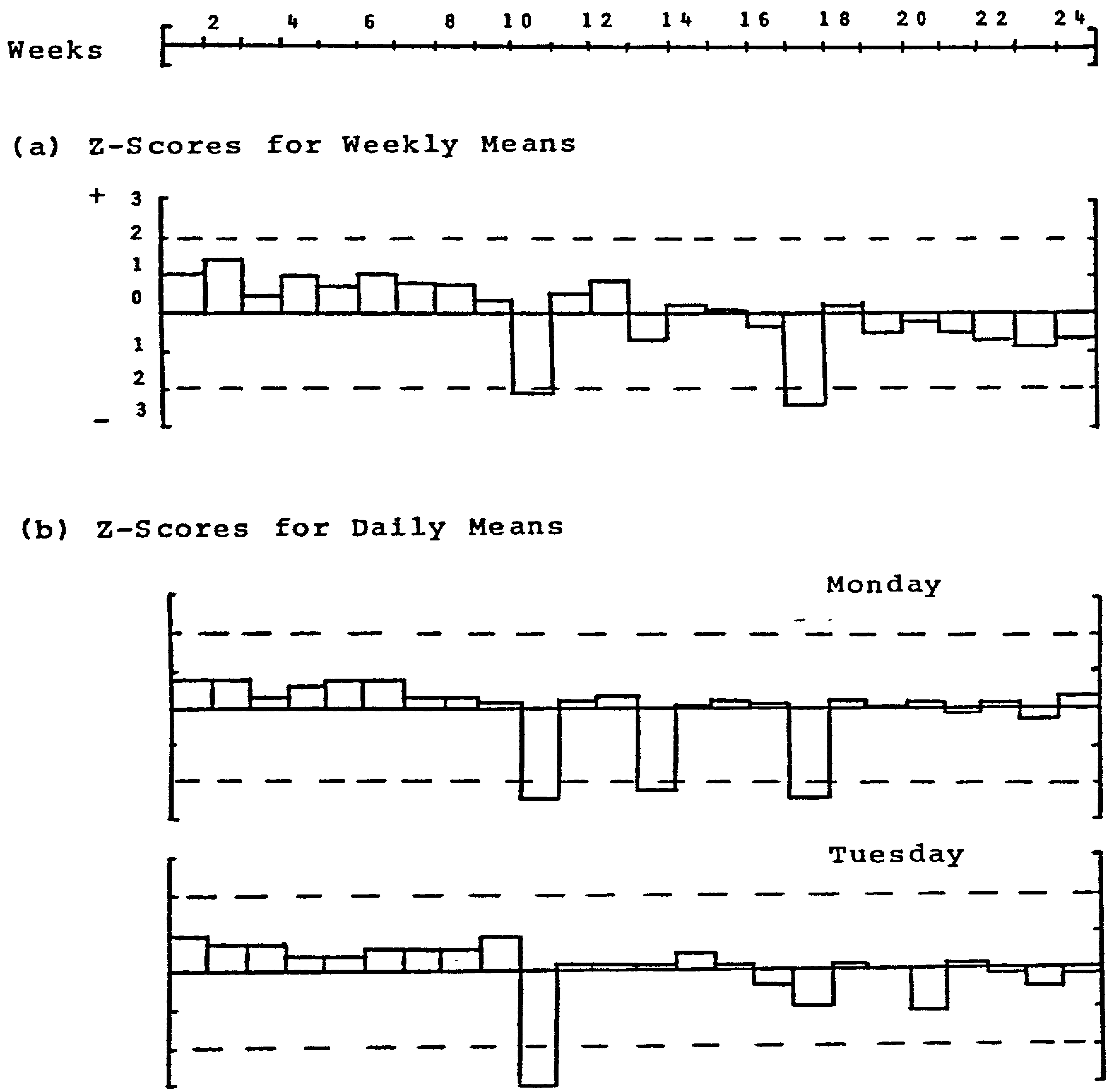
	Number of Shop Visits		Number of Shopping Trips		Expenditure on Goods £	
	Mean	SD	Mean	SD	Mean	SD
Whole Week	6.4	.43	4.5	.28	23	1.20
Monday	0.7	.23	0.5	.16	2	.52
Tuesday	1.0	.13	0.7	.08	3	.43
Wednesday	0.9	.08	0.7	.05	3	.26
Thursday	1.1	.08	0.8	.05	5	.56
Friday	1.3	.09	0.9	.05	6	.43
Saturday	1.2	.06	0.8	.03	5	.51
Sunday	0.2	.02	0.2	.02	0	.05

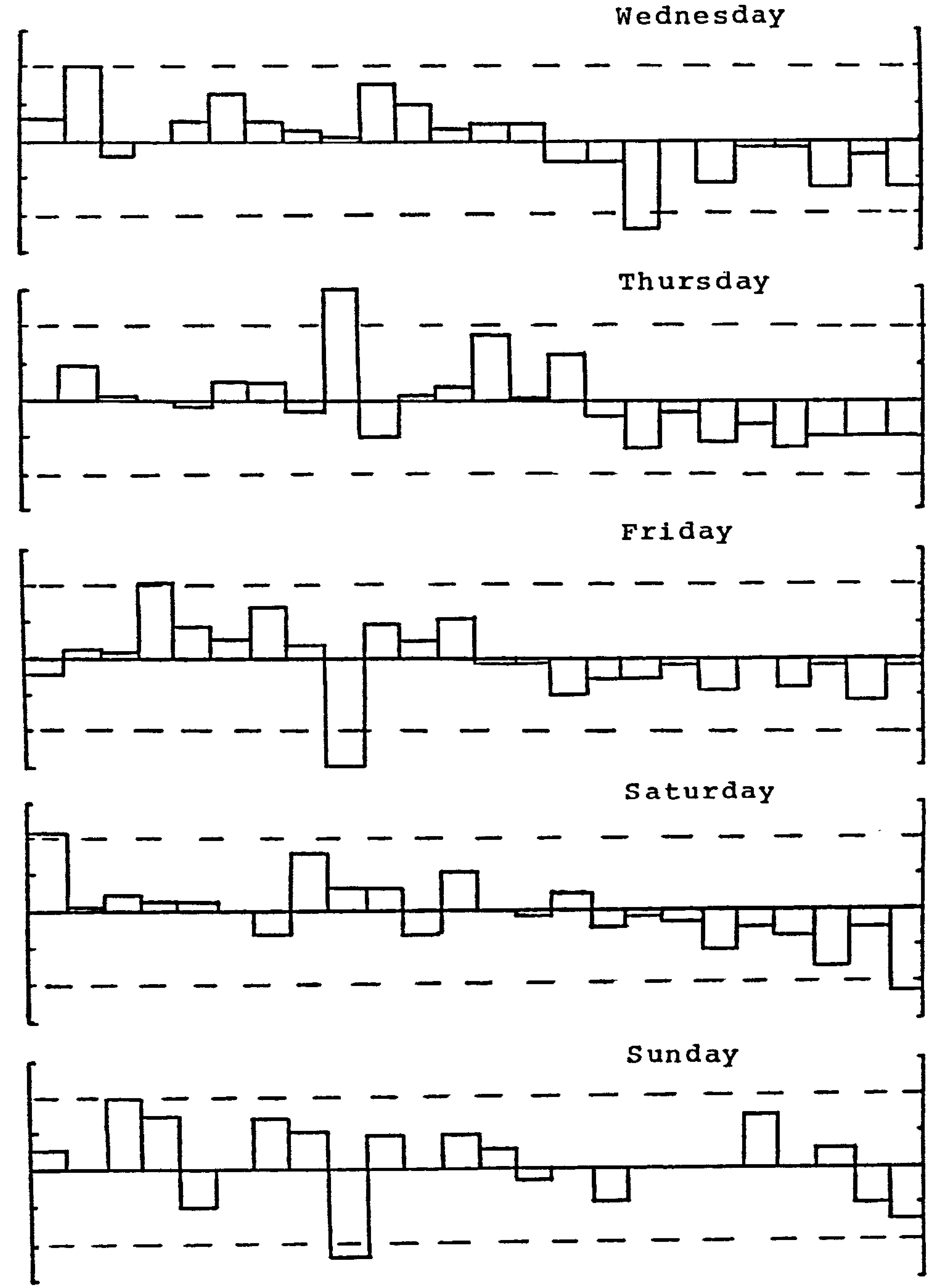
SD standard deviation

Figure 3.3

Analysis of Stability: The Mean Number of Grocery Shop Visits over 24 Weeks

(dashed line: 95% significance level)





- frequent contact was maintained between fieldworkers and panellists, thus the latter felt obliged to keep good records

- incentives were offered to maintain reliability and dedication

- diary forms were factual and could be completed automatically, this kept the workload light

- diaries were processed quickly so that omissions and blatant errors could be corrected while panellists were still participating on the panel

Second, the erratic record for Mondays is caused by the occurrence of public holidays. Three out of four bank holidays take place on Monday. Easter (week 10) has the greatest impact; on this date shop visits fall from a mean of 0.71 to 0.11 per consumer. If bank holidays are excluded from the record the mean number of shop visits on a Monday rises to 0.79 and the standard deviation is only 0.07 (a pattern much like any other day). Also associated with Easter is the exceptional rise in grocery purchases on Thursday of week 9; this arises from the accumulation of stocks prior to the public holiday. Special events can have an impact too; on Wednesday of week 17 a Papal Mass was held in Cardiff and this has influenced patterns of shopping.

Plots similar to figure 3.3 for expenditure also show the influence of public holidays, but there is no evidence of systematic trends. At this point it is useful to make a distinction between the absolute number of trips (where minor and major shopping events carry equal weight) and expenditure on trips (where major events dominate the picture). The absence of systematic trends in the pattern of expenditure suggests that major events are always recorded accurately; by contrast, the gradual decline in the absolute number of trips implies that minor events are subject to mis-recording.

These analyses have been repeated for many aspects of behaviour (such as mode choice, time of purchase, activities before and after shop visits) and in all cases the results are similar. Aggregate behaviour is stable. There are no dramatic trends over the 24 weeks, with the sole exception of a decline in the accuracy of records for minor events.

Apart from weekly variations there may be seasonal patterns of instability. The Cardiff panel started just after severe snowfalls during January 1982 and had finished before the July-August holiday period, so the main external influences (weather and vacations) did not have an impact. Unlike the purchase of durables and apparel, shopping for groceries and convenience goods is a task that continues throughout the year and, therefore, aggregate purchasing rates do not alter. Only among specific products would we expect to find marked seasonal patterns; for example, the purchase of ice cream and frozen desserts rises from a weekly mean of 102 items in February (month 1) to 177 items in July (month 6). Surprisingly, no other product field exhibits a steady trend, and even the purchase of fresh vegetables and fresh fruit shows a random distribution much like other goods.

For the duration of the Cardiff panel seasonality does not influence aggregate levels of activity. Only bank holidays have a large impact. The residual trend that exists is ascribed to a decline in the record of minor shop visits.

Market researchers are aware of the effect that recording bias can have on the accuracy of surveys. A particularly informative study is that of McKenzie (1983) who is able to measure bias directly; he compares telephone diary records from an 18-day surveillance period with the known number of calls (automatically recorded by line monitoring equipment) and finds that the accuracy of record-keeping rapidly declines. With increased use of longitudinal data, geographers and transport analysts are becoming aware of similar topics (Hanson and Huff 1982, Herz 1983). In all these studies there remains the problem that recording bias is intertwined with real trends in seasonal activity due to variable consumption patterns and the weather.

3.5 Analysis of Repetition

The purpose of this section is to establish whether consumer behaviour is repetitive. To do this, several components which describe shop visits are studied. The method involves the creation of contingency tables whose dimensions are components of shop visits. Cell-counts in these tables record the number of visits which occur during the surveillance period. It is suggested that if observations are concentrated into a few cells then there is evidence of repetitive behaviour, otherwise there is a random spread among cells and no repetition.

Shop visits are described by seven components; namely the time of purchase, form of travel, day of week, activity prior to grocery shopping, expenditure on grocery goods, the number of goods bought, and shop location. Most components are categorised in the same manner as that shown on the diary sheets (figure 3.2). Expenditure and purchases are partitioned into three groups (heavy/medium/light), and shop locations are counted separately for each consumer (during a sub-period of 35 days the maximum number of shops visited by a single consumer is 9).

The seven components are arranged into two-way contingency tables. An entry in each cell shows the frequency of occurrence across a 35-day surveillance period (February 8 to March 14, 1982). Thus, a cross-tabulation of time and mode might show a frequency count of 5 in the first cell, this would indicate that across 35 days there are 5 shop visits which occur during time slot 1 and where travel is by mode 1.

Geographical analysis is usually concerned with segments of a population (rather than individuals), therefore several distinctive groups of women shoppers have been studied. Here the results are illustrated by making reference to just 2 groups. Frequencies are counted for two groups of women who are in different stages of the life-cycle: (1) those in the pre-child phase and (2) those in the child-rearing phase. These samples, amounting to 21 and 32 women respectively, are internally homogeneous and are expected to reveal different patterns of repetitive behaviour.

After cell frequencies have been tabulated, values that concentrate into a few cells need to be distinguished from a purely random spread. Several indices are employed to measure the amount of concentration, these are:

(1) the number of cells with more than 10% of visits

(2) the number of cells with at least one entry

(3) the proportion of visits in the cell with most entries

The ten percent cut-off in (1) isolates the distribution of the most significant shop visits, whereas the count in (2) indicates the distribution of visits from among the whole range of possibilities. Finally, a measure of heavy concentration is obtained from values in the largest cell (3). If behaviour is repetitive the first two indices should yield small values (ie. few cells are occupied), while the third index should give large percentage values.

Results are presented in table 3.4 (a) and (b). Contingency tables contain a maximum of 15 to 35 cells, yet the majority of these are relatively empty. The number of cells with more than 10% of visits is small, with a norm of about three. Cells where at least one visit is recorded number about 6 to 9, which means that at least 50% are empty. Cross-tabulation of mode versus time, for instance, shows that out of 30 cells in the contingency table only 7 are occupied. In general, between one half and three-quarters of the cells are empty. Finally, between a third and one half of all visits are described by one interaction in each contingency table. If we reconsider the cross-tabulation of mode versus time, then 37% of shop visits are in a single cell.

These results show that shopping travel is repetitive. This is true not just in aggregate terms, but also in relation to the components of travel such as form of travel, timing and expenditure.

Mean values for the two samples of women are remarkably similar. Comparison of sample means (table 3.5) emphasises that there is no significant difference between the two samples. The only consistent exceptions appear in the contingency tables for activity versus mode, and mode versus shop location. Women who care for children have less choice over the form of travel and face a narrower range of shopping opportunities, whereas working women in the pre-child phase have wider transport options, visit more shops and engage in varied activities. Given that results from both samples are broadly similar, the interpretation of these exceptions must be guarded.

The analysis above has shown that behaviour is repetitive and that broadly this is true for different segments of the population. Perhaps slightly different results would arise if the boundary of each category was altered or if indices of concentration were defined in another way, but most social science handles 'lumpy' data and therefore boundary problems are unavoidable.

Table 3.4 (a)

Analysis of Repetition:
Features of Shopping Travel over 35 Days

(a) Sample of Women Consumers in the Pre-Child Phase N = 21

Contingency tables				Number of cells with more than 10% of stops		Number of cells with at least one stop		Percent value of largest cell	
Table	Dimensions	Number of cells		$\bar{X}$	SD	$\bar{X}$	SD	$\bar{X}$	SD
time * mode		6*5	30	3	1.1	7	1.8	37	12.0
day * mode		7*5	35	4	1.3	8	2.4	33	13.6
activity * mode		5*5	25	3	0.9	5	1.5	42	12.2
activity * time		5*6	30	4	1.8	8	3.1	30	12.7
expenditure * mode		3*5	15	3	1.2	5	0.9	50	13.8
expenditure * time		3*6	18	4	1.5	9	2.1	29	8.6
expenditure * activity		3*5	15	4	1.6	7	1.8	35	11.1
purchases * mode		3*5	15	3	1.2	5	1.1	53	17.0
purchases * time		3*6	18	4	1.7	8	1.9	30	8.7
purchases * activity		3*5	15	4	1.6	7	1.9	35	11.7
mode * shop location		5*v	v	3	1.2	6	2.0	47	17.7
time * shop location		6*v	v	3	1.4	9	3.2	31	9.9
activity * shop location		5*v	v	3	1.4	8	2.8	34	10.6

$\bar{X}$ mean
SD standard deviation

Table 3.4 (b)

Analysis of Repetition:
Features of Shopping Travel over 35 Days

(b) Sample of Women Consumers in the Child-Rearing Phase N = 32

Contingency tables: Table Dimensions		Number of cells	Number of cells with more than 10% of stops: $\bar{X}$	SD	Number of cells with at least one stop: $\bar{X}$	SD	Percent value of largest cell: $\bar{X}$	SD
time * mode	6*5	30	3	1.0	6	2.1	46	17.2
day * mode	7*5	35	5	1.3	8	2.0	28	9.6
activity * mode	5*5	25	3	1.1	5	2.3	58	20.6
activity * time	5*6	30	3	1.1	9	3.5	35	16.4
expenditure * mode	3*5	15	3	0.9	4	1.6	54	16.0
expenditure * time	3*6	18	3	1.2	9	2.2	32	12.6
expenditure * activity	3*5	15	4	1.2	7	2.4	40	15.5
purchases * mode	3*5	15	3	0.9	5	1.7	50	12.8
purchases * time	3*6	18	4	1.0	9	2.6	29	11.9
purchases * activity	3*5	15	3	1.0	7	2.3	38	13.3
mode * shop location	5*v	v	2	0.9	5	2.6	64	17.9
time * shop location	6*v	v	3	1.3	9	3.6	37	12.4
activity * shop location	5*v	v	3	1.1	7	3.6	47	17.9

$\bar{X}$ mean
SD standard deviation

Table 3.5

Analysis of Repetition:
Features of Shopping Travel over 35 Days

Comparison of Sample Means

Sample of women consumers in the pre-child phase $N_1 = 21$
Sample of women consumers in the child-rearing phase $N_2 = 32$

Contingency tables	Number of cells with more than 10% of stops	Number of cells with at least one stop	Percent value of largest cell
	t-value	t-value	t-value
time * mode	1.0	1.5	2.4 *
day * mode	1.8	0.2	1.4
activity * mode	2.4 *	1.6	3.6 **
activity * time	0.6	0.1	1.3
expenditure * mode	1.4	0.9	1.1
expenditure * time	0.4	0.1	1.4
expenditure * activity	0.0	1.0	1.4
purchases * mode	0.6	0.5	0.8
purchases * time	0.3	1.6	0.4
purchases * activity	1.3	0.6	0.9
mode * shop location	2.4 *	2.2 *	3.5 **
time * shop location	0.7	0.2	2.0 *
activity * shop location	1.5	1.8	3.4 **

Tabulated two-tailed t-statistics for $N_1 + N_2 - 2$ degrees of freedom:

*	95% significance level	2.01
**	99% significance level	2.68

Earlier studies of panel data also found that components of travel are repetitive and habitual (Marble and Bowlby 1968, Hanson and Huff 1982). A direct comparison can be made between results from Cardiff and Uppsala because the surveillance periods are alike (recall that the study of repetition in Cardiff has been confined to a sub-period of 35 days). Results are consistent in both cases: (1) relatively few cells in the contingency tables contain most of the travel events, and (2) there is little difference between the behaviour of those who work outside the home and those who do not. The only possible exception to (2) is when work status and travel mode are considered together.

Coincidentally a study of store loyalty in Cardiff led to similar conclusions (Dunn and Wrigley 1984b). If we regard 'shop location' as a measure of store loyalty, then our discovery that behaviour is repetitive implies that shoppers are loyal to relatively few shops. This accords with the findings by Dunn and Wrigley that the average household makes 42% of grocery purchases at a single store, and that the least loyal group of consumers is young and without children, whereas the most loyal are those without a car.

3.6 Households versus Consumers

When a person plans to do something reference is made to other people's wishes. Personal plans have to be reconciled with the family, workunit, and so on. Thus, the decision to go shopping may be influenced by the need to meet children from school or to prepare meals for other members of the family. To evaluate these interactions many other people would need to record their behaviour. But it is unrealistic to hope that all members of a family, friends, workmates and relations would be willing to keep diaries. In fact, most surveys concentrate on households or consumers, and the practical problem is to decide whether household records or consumer records should be studied.

On every diary sheet panellists were asked to indicate who made the purchase (ie. whether it was the panellist, other household member, or non-household member). The occurrence of non-household members is small so the major distinction is between the two other categories. In the case of the Cardiff panel only principal shoppers are panellists, whereas in some surveys all members of the household are included on the panel; this difference will influence whether household records or consumer records are studied.

Several measures of activity are tabulated in table 3.6 (a) and (b) to compare data for households and consumers. Attention is given to the different magnitudes and percentages (their precise meaning is not important at this stage). A shift from household to consumer data results in the loss of 427 visits, or 13% fewer visits on average per week. Similarly, there are 15% fewer trips when consumers alone are observed.

Changes among records of goods bought and expenditure are less important. The impact amounts to a 7% decline, which implies that while other members of the household do visit shops the amount that they purchase on each occasion is small. Averages per panellist (table 3.6 (b)) support these comments. Grocery shop visits fall from 7.2 per panellist each week when all

Table 3.6 (a)

Households versus Consumers:
Comparison of Shopping Features over 24 Weeks, Whole Panel

(a) Average numbers per week

451 Panellists	All Shopping Events				Major Shopping Events			
	Households		Consumers		Households		Consumers	
	No	%	No	%	No	%	No	%
Shop visits:	3243		2816		972		892	
Monday	360	11	309	11	53	5	48	5
Tuesday	506	16	449	16	110	11	103	12
Wednesday	455	14	397	14	97	10	90	10
Thursday	566	17	500	18	196	20	184	21
Friday	626	19	561	20	267	27	249	28
Saturday	633	20	535	19	244	25	215	24
Sunday	97	3	66	2	5	1	4	0
		100		100		100		100
Shopping trips:	2322		1979		564		512	
Single-stage	1728	74	1434	72	336	60	300	59
Multi-stage	594	26	545	28	228	40	212	41
		100		100		100		100
Goods bought	14932		13851		8909		8273	
Expenditure £	11052		10278		7118		6609	

Major events are defined when expenditure exceeds £5.50
and when more than 6 goods are bought.

Table 3.6 (b)

Households versus Consumers:
Comparison of Shopping Features over 24 Weeks, per Panellist

(b) Average numbers per panellist per week

451 Panellists	All Shopping Events		Major Shopping Events	
	Households	Consumers	Households	Consumers
Shop visits:	7.2	6.2	2.2	2.0
Monday	0.8	0.7	0.1	0.1
Tuesday	1.1	1.0	0.2	0.2
Wednesday	1.0	0.9	0.2	0.2
Thursday	1.3	1.1	0.4	0.4
Friday	1.4	1.2	0.6	0.6
Saturday	1.4	1.2	0.5	0.5
Sunday	0.2	0.1	0.0	0.0
Shopping trips:	5.1	4.4	1.3	1.1
Single-stage	3.8	3.2	0.7	0.7
Multi-stage	1.3	1.2	0.5	0.5
Goods bought	33	31	20	18
Expenditure £	25	23	16	15

Major events are defined when expenditure exceeds £5.50
and when more than 6 goods are bought.

household records are included to 1.2 when just consumer records are used, whereas purchases and expenditure hardly change.

For the analyses that follow information about components of activity and travel (such as day of week and the number of stages on a trip) are relied upon. Under these circumstances it is important to know whether the proportion in each sub-category is seriously affected by the choice of recording unit. In general, the decision of whether to study households or consumers does not alter the proportion found in each sub-category. Thus, 11% of visits occur on Monday regardless of whether household records or consumer records are utilised. This conclusion remains true where only major events are included and where the Cardiff sample is divided into life-cycle groups. For instance, irrespective of whether household or consumer records are studied 5% of major visits occur on Monday.

Records returned by consumers are the main source of information for the studies that follow. Several reasons lie behind this decision to rely on consumer records rather than those for the whole household. First, consumers are more conscientious and more reliable than other members of a household. It is consumers who have been briefed and who are dedicated to recording all their shopping movements, whereas other members might be casual about completing diary sheets. Second, many details are collected about the social background of consumers, whereas less is known about other members of the household. Personal circumstances, attitudes and patterns of movement are documented for individuals in a way that is unequalled.

Given that many proportions are about the same irrespective of whether households or consumers are the focus of attention, the decision to confine analysis to the latter should not raise difficulties. Possibly there are two exceptions:

(a) when, because of illness, elderly shoppers rely on neighbours and friends to perform errends, and

(b) when responsibility for shopping is shared equally among all members of the family.

In both these exceptional cases the very notion of a 'principal shopper' is misleading. Future panel surveys will have to take greater note of these exceptions if the population of Britain continues to age and if social roles change.

4 Discussion

The reliability of subsequent analyses depends on the quality of our original data. This concern with reliability has motivated a study of whether the Cardiff panel data are contaminated. Overall, the methodological study gives us much confidence and provides a good foundation for future work. It is clear that those who administered the panel made every effort to obtain a clean, representative and accurate set of data.

Stated briefly, the study of methodology shows that:

- panel recruitment is extremely arduous and recruitment rates in Cardiff are (like others) rather low
- minor sampling biases exist between panel members and non-panellists
- attrition is large at first but rapidly falls off, and is much lower than in comparable panel surveys
- married women aged 25-45 are easier to attract onto the panel than are singles, the elderly, those working full-time, and those without a car
- there is no evidence of systematic ordering effects in the completion of diary sheets
- the main features of consumer behaviour are stable throughout the study period and there is no systematic decline in the accuracy of reporting rates
- most aspects of shop visiting and trip-making are repetitive
- there are sizable absolute differences when definitions are altered, but proportions remain the same irrespective of which definition is used

These conclusions do not convey a consistent message: initial recruitment is arduous whereas problems due to attrition are less than originally expected. Even where there are unavoidable problems, however, panel data offer tremendous advantages over alternative survey designs. Being disaggregate, panel data give a detailed picture of activity, movement and behaviour over a lengthy period of time. The methodology removes many of the reporting errors associated with cross-sectional surveys because less reliance is placed on imperfect memory recall and because diary completion can become automatic and routine. Finally, the problems of open-ended time-budget surveys are avoided if diary sheets are laid out in a standard format and if panellists are carefully briefed.

Often the question of data quality is quietly neglected. Yet this chapter has provided more than enough evidence to show that if sophisticated models are to be estimated with confidence then survey design must be addressed. This issue is beginning to be recognised in geographical research (Brög and Meyburg 1983, Wrigley et al. 1985). With greater interest in longitudinal data analysis it is to be hoped that some of the methodological impasses will be resolved and that sources of error will be reduced still further.

CHAPTER 2

DESCRIPTION AND CONSUMER ACTIVITY

Those who have handled sciences have been either men of experiment or men of dogmas. The men of experiment are like the ant, they only collect and use; the reasoners resemble spiders, who make cobwebs out of their own substance. But the bee takes a middle course; it gathers its material from the flowers of the garden and of the field, but transforms and digests it by a power of its own.

Francis Bacon (1620)
'Novum Organum'

1 Aspects of Grocery Shopping: Summary Features

The basic features of grocery shopping are described in the initial part of this chapter. There are no universally agreed rules for the study of movement, therefore a number of conventions are used to give working definitions. Next, frequencies are described. Frequencies express the rhythms of behaviour which operate at weekly, daily and diurnal scales. Patterns of shop visiting, expenditure and purchasing are locked into these temporal rhythms in distinctive ways. The section concludes with a look at shopping as an activity. Attention is drawn to the importance of food shopping in family budgets and how this activity relates to the pursuit of other activities in urban areas.

1.1 Definitions

Any descriptive account of behaviour needs a set of working definitions. No universally agreed definitions are available, so the ones listed below are justified solely in terms of precedent and by what seems to be reasonable.

There are two main definitions:

(1) Shop visits

A shop visit is a distinct shopping event which is separate from other events. This isolated happening is equivalent to the purchase occasion used in studies of brand choice and repeat-buying. For the purpose of measurement, only shop visits which result in the purchase of groceries are recorded (browsing and bargain-hunting are not observed). From an activity viewpoint the notion of a shop visit is dimensionless. It fails to capture information about linkages between a visit to one shop and another, or between different forms of consumer activity.

(2) Shopping trips

Trips represent the round journey from one distinct activity (or location) to another distinct activity (or location). At least one component will involve patronage of a shop, but the trip may originate at (or be destined for) the consumer's home, workplace, school, or any other place in the urban area.

Because several shops may be visited on one trip it is important to distinguish between:

(a) Multi-Stage trips

Multi-stage trips occur when several shops are visited on one trip. A further condition is that these visits are consecutive.

(b) Multi-Purpose trips

Multi-purpose trips are defined when grocery shopping is combined with other distinct activities. The activity undertaken at the origin and/or destination of a trip is used to define these multi-purpose trips.

In addition to a count of absolute numbers of visits and trips it is often relevant to consider how many goods are bought on each occasion and what amount of money is spent. The number of goods is indicated by panellists when they complete their diaries, however the number of packets is not mentioned. A visit to a freezer centre to buy 10 kg of sausages, for example, will carry equal weight as a visit to a butcher to buy 2 kg of sausages. Records of expenditure partially correct for the packet-size problem, and in subsequent sections expenditure is used to 'weight' counts of visits and trips.

Variation in the definition of terms means that comparisons between surveys are fraught with danger. Notwithstanding the practical difficulty of making comparisons, several times reference is made to the Watford activity survey (Daws and McCulloch 1974). This survey is close in spirit to the Cardiff panel, especially when trip frequencies and movements are studied. In November 1969, when the Watford panel was in operation, the population of the Borough stood at about 170,000: a figure that compares with 274,000 in Cardiff district in 1981. Clearly, Cardiff is a much larger place, although local community ties may be stronger. In terms of retail development - number of superstores, pedestrian precincts, planned centres - Watford was in advance of Cardiff by 1969 but the Welsh capital has more than caught up during the past decade.

Results of the initial analysis are presented as a series of commentaries. Special attention is given to weekly, daily and diurnal rates of grocery shopping, and to various aspects of multi-linked activity.

1.2 The Frequency of Grocery Shopping

1.2.1 Weekly Rates

Each week just over 2800 grocery shop visits are recorded by the 451 consumers on the Cardiff panel, this gives an average frequency of 6.2 shop visits per consumer per week. Since it is common for several shops to be visited on one trip the frequency of trips is much lower. There are in fact almost 2000 trips each week and the average frequency stands at 4.4 trips per consumer.

Over the period of one week the typical consumer buys 31 grocery goods at a cost of £23. Stated another way, on each shop visit 4.9 goods are bought and these purchases sum to an expenditure of £3.60 (table 1.1).

Hidden in these averages is a considerable amount of variation. Some consumers undertake many minor trips, others are shopping infrequently. The sample frequency distributions in table 1.2 reveal the extent of variation. Observed most frequently are those

Table 1.1

Aspects of Grocery Shopping:
Weekly Averages over 24 Weeks (Summary Measures)

451 Consumers	Average number per week	Average number per consumer per week
Grocery shop visits	2816	6.2
Shopping trips	1979	4.4
Goods bought	13851	31
Listed expenditure £	10278	23
Goods bought per visit	4.9	
Goods bought per trip	7.0	
Expenditure per visit £	3.60	
Expenditure per trip £	5.20	

Table 1.2

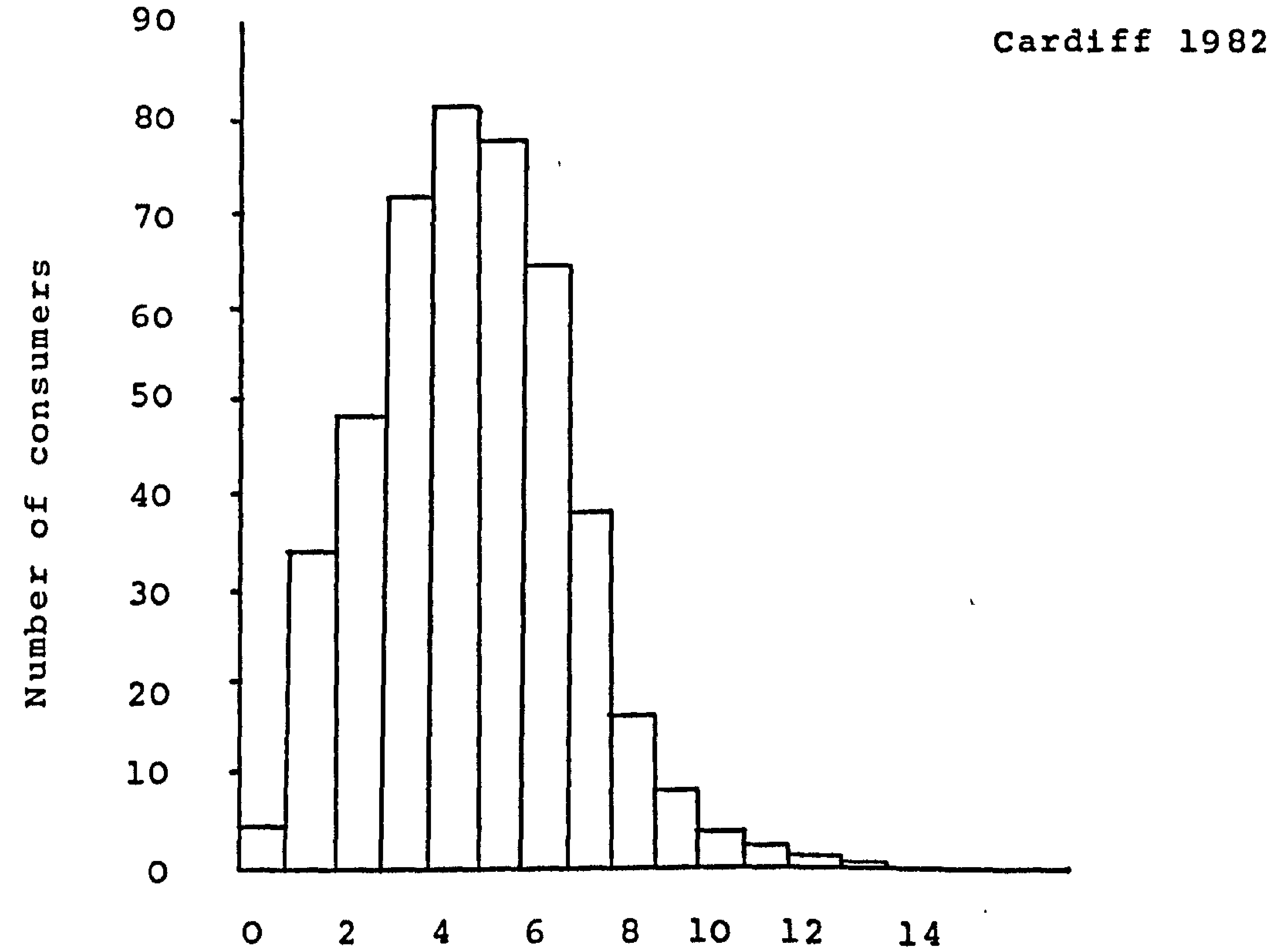
Aspects of Grocery Shopping:
Weekly Averages over 24 Weeks

Sample Frequency Distributions

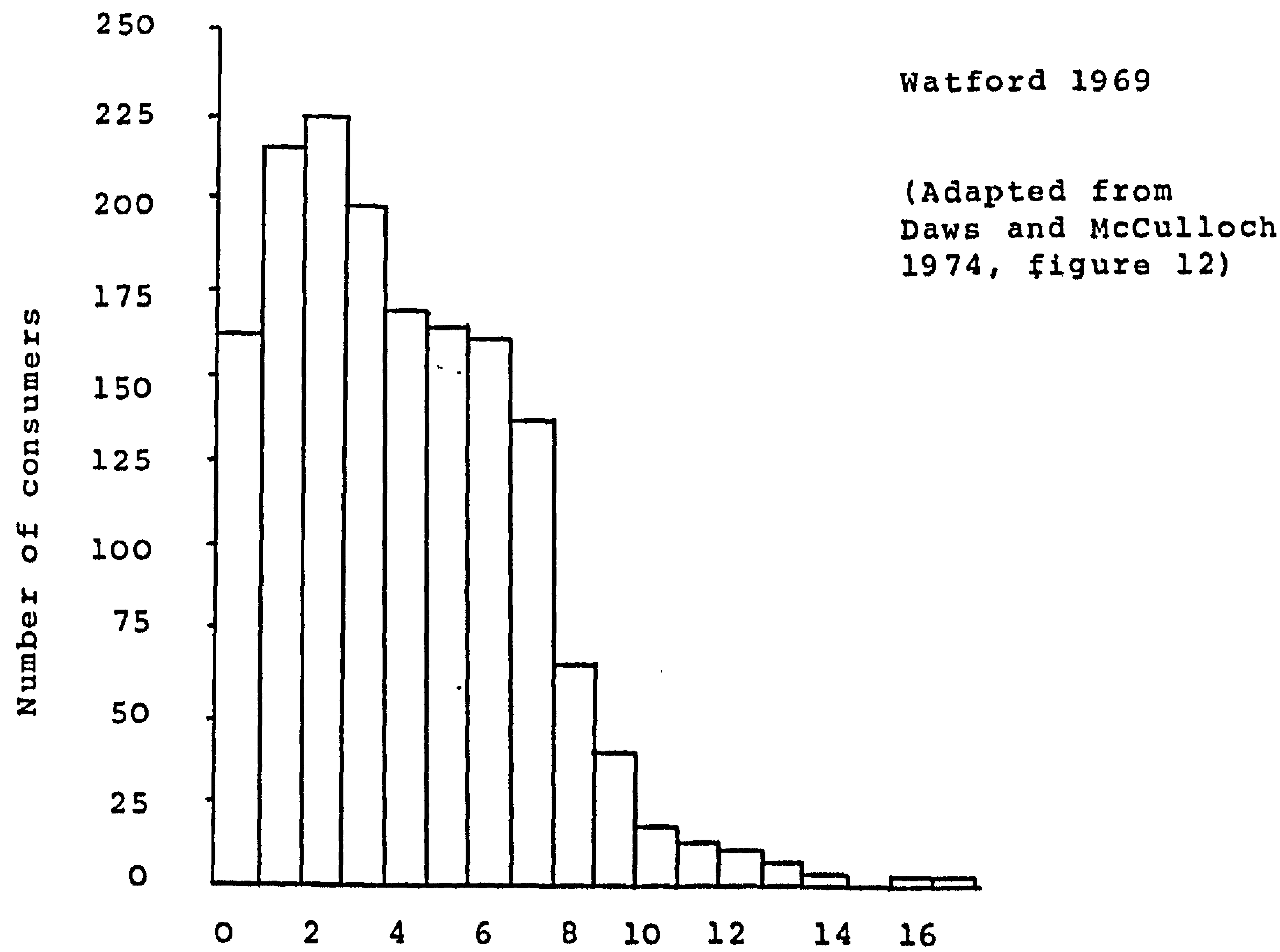
Number of shopping trips per week	Average number of consumers in each group	Percent of all consumers in each group	Average number of shopping trips involved	Percent of all shopping trips in each group
0	4.3	1	0.0	0
1	34.5	8	34.5	2
2	48.1	11	96.1	5
3	72.3	16	216.9	11
4	82.6	18	330.3	17
5	77.1	17	385.6	19
6	64.5	14	386.8	20
7	37.5	8	262.6	13
8	16.3	4	130.7	7
9	7.7	2	68.8	3
10	3.3	1	32.6	2
11	1.7	0	18.9	1
12	0.8	0	10.1	1
13 +	0.3	0	4.7	0
	451	100	1979	100

Figure 1.1

Comparison of Cardiff and Watford Consumer Panels:
Average Sample Frequency Distributions



Average number of shopping trips per week



Shopping trips per week

who undertake 4 trips per week; this rate of trip-making is characteristic for about 18% of the sample. Typically, most shoppers are making 3 to 5 trips every week. Only 1% fail to record any events - these are people absent from the panel because of holidays or who buy in bulk once a month at a hypermarket. Even among the latter group several 'emergency' visits to grocery shops are likely. At the other extreme are about 6% of the sample who claim to make more than 10 trips. Those who state such high trip frequencies normally live near convenient neighbourhood shops.

Another way to view these figures is to consider the distribution of trips. Some 20% of trips are concentrated among shoppers who make 6 trips per week.

Having summarised weekly rates of grocery shopping it is useful to compare findings from Cardiff in 1982 with those from earlier surveys. Generally the number of trips in Cardiff is about 0.5 above the rates reported in earlier surveys. For instance, in Watford during 1969 3.9 shopping journeys per person per week were recorded (Daws and McCulloch 1974). More recent evidence comes from the 1978-79 National Travel Survey (Department of Transport 1983), this shows 4.7 shopping journeys per person per week.

Sample frequency distributions for Cardiff and Watford are compared in figure 1.1. Up the vertical axis is the absolute number of consumers and along the base are trip frequencies. The modal group in Cardiff is 4 trips, which compares with 2 trips in Watford. In both cases the upper limit is about 7 trips per week. Despite a similar range of values, the Watford results are distinctly skewed towards lower rates of trip incidence.

Two caveats need to be mentioned when these comparisons are made: (1) the definitions of trip/journey that are closest to one another are used here, but important differences remain; (2) many earlier studies do not distinguish between grocery shopping and journeys to buy clothes, appliances and sometimes include visits to lauderettes, betting shops and petrol stations. When these caveats are taken into account a figure of 4.4 trips for grocery shopping (alone) is high and needs to be explained.

There are several reasons why trip rates in Cardiff are higher than those reported in earlier studies. (a) Participants on the panel were asked to record all events, including many emergency purchases on Sunday, goods bought from mobile traders and walk-based trips. Often these aspects are ignored in large-scale surveys. (b) Many records contain very minor purchases - such as single visits to buy soft drinks, a loaf of bread or crisps - such activity is time consuming but not economically important. (c) The diary page contained a box to be checked if no listed items were bought on a particular day; this technique substantially aids the reporting of minor events. (d) The diary method aims to maintain a complete and continuous record. Far less reliance is placed on memory recall, so more events are likely to be recorded.

The superiority of diary methods is illustrated if responses from an initial questionnaire are compared with diary records. Respondents who agreed to join the panel were asked to recall: 'about how many times a week do you normally buy groceries?' Some 33 people said that their trip frequencies varied from week to week. Of the remaining 572 respondents 45% said 2 or fewer trips were undertaken. In fact the distribution of recollected trips is bimodal, with about 23% saying one or fewer trips per week and a similar proportion saying 6 or more. Compare these rates against those in table 1.2. Only 9% of shoppers actually record one or fewer grocery trips per week and more than 29% list 6 or more. The fuller record obtained from diaries gives quite different results from questionnaire methods.

1.2.2 Daily Rates

If all types of activity are grouped together fairly uniform frequencies are obtained over the period Monday to Friday. Grocery shopping is different. There is a steady rise in shopping activity as the weekend is approached.

Presented in table 1.3 are daily averages for grocery shop visits, shopping trips, goods bought and listed expenditure. Whichever measure is considered the peak on Friday is unmistakable. Some 561 shop visits happen on Friday, this gives an average rate of 1.2 visits per consumer. Expenditure on these occasions amounts to £5 per consumer, the money being spent on 6 products. The magnitude of these averages rises slightly if expenditure and purchases are expressed on a per-trip basis.

After Friday, Saturday and Thursday are the next most important days. To appreciate just how concentrated is shopping activity it is worth noting that 57% of shop visits occur within the period Thursday to Saturday. In terms of goods bought and expenditure the concentration effect is even more marked: 68% and 71% respectively. Implied by these figures is a tendency for major events to occur during the latter part of each week, it is then that bulk-purchasing can be done under one roof at superstores and freezer centres.

Two cultural factors deserve mention: early closing and Sunday trading. Wednesday is of less importance - accounting for only 14% of shop visits and averaging only £2.70 per visit - because traders close early. Early closing one day a week used to be a universal practice in British towns, now it is often confined to local shops and independent proprietors.

Sunday trading is restricted in England and Wales under the terms of the Shops Act 1950. While many goods cannot be sold on Sunday it is perfectly legal to sell confectionary, fresh fruit and vegetables, and fresh dairy products, and many ethnic traders take advantage of this opportunity. Each week about 65 shopping trips, or 3% of the total, are undertaken on Sunday. Some 2.4 goods are bought per trip. On each occasion expenditure is light, being no more than £1.40. Economically Sunday buying is unimportant, though perhaps it is more widespread than expected and more common than the provisions of the Shops Act intend.

Comparison of figures from Cardiff and Watford gives broadly similar conclusions. The only significant difference is that rates for Friday and Saturday are swapped around. In Cardiff the single most important day is Friday (19% of all shopping trips) followed by Saturday (18%); whereas Saturday is most important in Watford (23%) which is trailed by Friday (19%). To a limited extent

Table 1.3

Aspects of Grocery Shopping:
Daily Averages over 24 Weeks

451 Consumers	Mon	Tues	Wed	Thur	Fri	Sat	Sun
(a) Average number per day:							
Shop visits	309	449	397	500	561	535	66
Shopping trips	236	310	288	356	375	347	65
Goods bought	1133	1727	1594	3006	3541	2695	155
Expenditure £	676	1140	1089	2230	2801	2252	90
(b) Average number per consumer per day:							
Shop visits	0.7	1.0	0.9	1.1	1.2	1.2	0.1
Shopping trips	0.5	0.7	0.6	0.8	0.8	0.8	0.1
Goods bought	2.5	3.8	3.5	6.7	7.9	6.0	0.3
Expenditure £	1.5	2.5	2.4	4.9	6.2	5.0	0.2
(c) Average per visit per day:							
Goods bought	3.7	3.8	4.0	6.0	6.3	5.0	2.3
Expenditure £	2.2	2.5	2.7	4.5	5.0	4.2	1.4
(d) Average per trip per day:							
Goods bought	4.8	5.6	5.5	8.4	9.4	7.8	2.4
Expenditure £	2.9	3.7	3.8	6.3	7.5	6.5	1.4
(e) Percent of average weekly total (100%):							
Shop visits	11	16	14	18	20	19	2
Shopping trips	12	16	15	18	19	18	3
Goods bought	8	13	12	22	26	20	1
Expenditure	7	11	11	22	27	22	1

Cardiff shows a flatter distribution: there are fewer trips on Saturday and more on Tuesday and Wednesday.

Quite why there are differences is not easy to decide; either the sample areas differ in important ways (of those Watford residents who worked one quarter travelled beyond the Borough and might find it hard to shop during weekdays), or patterns of behaviour have changed over the 1970s (early closing is less common). Interestingly 3.5% of shopping trips in Watford occurred on Sunday, a percentage not too dissimilar from the latest figures and certainly not a finding to suggest dramatic change in volumes of Sunday trading over the past decade.

1.2.3 Diurnal Rates

Aspects of grocery shopping are separated into time-slots in table 1.4. About 12% of trips occur before 10 am, thereafter the frequency rises until noon. There is a lunchtime lull which is followed by a secondary peak during the early afternoon 2 pm to 4 pm. The number of trips recorded after 4 pm is similar to the number before 10 am.

With 38% of trips, the period 10 am to noon plainly is dominant. Over 700 trips occur, and on each 7.3 products are bought at a cost of £5.20. This period is known to be preferred by many pensioners and mothers with young children.

A contrast is to be drawn between early morning and late-night activities. Early morning trips number no more than 225 events, and only a small number of goods are bought (less than 6 items at a cost of £4). Most shoppers will try to avoid this period because roads are congested with commuter traffic and delivery lorries. In percentage terms, rates of activity after 4 pm are no more important than those recorded earlier, however far more goods are bought per trip. Indeed, only 50 trips take place after 6 pm, but these average almost 12 goods which cost £9.60 - evening consumers are buying in bulk.

The distribution of trips across days of the week tends to become concentrated as time progresses. If, for instance, 16% of trips occur on Monday before 10 am then about 16% will occur on Tuesday at the same time; ie. percentages across weekdays remain fairly constant during the morning period. In contrast, only 7% of trips after 6 pm are recorded on Monday in comparison with 35% of such trips recorded on Friday and 29% on Thursday. In fact, evening shopping has a minor role on all days except Thursday and Friday.

Two factors combine to channel activity into Thursday and Friday evenings. First, there is the effect of the purchasing cycle: provisions are accumulated before the weekend break, whereas immediately after the break further purchases are unlikely. Second, there are more opportunities to buy groceries on Thursday and Friday because shops tend to open late, this is particularly true of superstores, freezer centres and discount stores.

Roughly similar findings have been presented in earlier surveys. A comparison of the diurnal pattern in Cardiff against transport surveys in Norwich and Northampton shows a bimodal distribution in all cases: a primary peak during mid-morning, followed by a lunchtime lull, and then a secondary peak in the early afternoon

Table 1.4

Aspects of Grocery Shopping:
Diurnal Averages over 24 Weeks

451 Consumers	Before 10 am	10 am Noon	Noon 2 pm	2 pm 4 pm	4 pm 6 pm	After 6 pm
(a) Average number per time period:						
Shopping trips	225	735	364	399	179	50
Goods bought	1252	5366	2391	2827	1298	578
Expenditure £	901	3798	1810	2117	1053	482
(b) Average number per consumer per time period:						
Shopping trips	0.5	1.6	0.8	0.9	0.4	0.1
Goods bought	2.8	11.9	5.3	6.3	2.9	1.3
Expenditure £	2.0	8.4	4.0	4.7	2.3	1.1
(c) Average per shopping trip per time period:						
Goods bought	5.6	7.3	6.6	7.1	7.3	11.6
Expenditure £	4.0	5.2	5.0	5.3	5.9	9.6
(d) Percent of average weekly total (100%):						
Shopping trips	12	38	19	20	9	3
Goods bought	9	39	17	21	9	4
Expenditure	9	37	18	21	10	5

Table 1.5

Comparison of Diurnal Rates of Shopping:
Cardiff, Norwich and Northampton

Time periods	Before 10am	10am Noon	Noon 2pm	2pm 4pm	4pm 6pm	After 6 pm	
Cardiff 1982	11	37	19	21	10	3	100
Norwich 1967	14	31	14	16	18	7	100
Northampton 1964	21	20	18	28	11	2	100

All figures are percentages for an 'average' weekday (Monday to Friday)

Pedestrian trips are included in all surveys

Cardiff panel 1982: averages over 24 weeks, grocery shopping only

Norwich transport survey 1967: all shopping, percentages are calculated from counts at hourly intervals (source: Daniels and Warnes 1980, figure 3.2)

Northampton transport survey 1964: all shopping, percentages are calculated from counts at half-hourly intervals (source: Daniels and Warnes 1980, figure 3.1) (table 1.5). These conventional patterns appear to be rigid and are reinforced by trading laws (ie. the Shops Act 1950) and employment legislation. Also, temporal patterns are influenced by the opening hours of schools, workplaces, clinics and post offices. Hillman et al. (1976) stress how morning shopping is dominant because several activities can be combined; the elderly can collect their pensions and young mothers can visit clinics and take young children to school.

The only major change apparent over the past 20 years is a shift in morning activity from 9 am to 11 am. For instance, 15% of all shopping trips in Northampton took place between 9 am and 10 am, by 1982 in Cardiff only 11% of trips happened before 10 am. There may be several social reasons for such a change. Local markets - which start early - are less important elements of the retail scene, which means that the opportunity for early morning buying is unavailable today. Possibly the rise in commuter traffic has acted as a deterrent since it is unpleasant and a hassle to shop in crowded streets which are filled with slow-moving traffic. Off-peak bus fares and parking controls would also shift non-work activity away from rush hours.

Two cautionary words must be added because survey design and local circumstances will affect our interpretation of retail change. The Norwich and Northampton surveys included all forms of shopping activity at a fine level of detail (hourly and half-hourly intervals), so comparisons with coarse figures from Cardiff are less than perfect. Secondly, local circumstances are important. Grocery markets remain important in some cities and these will continue to attract early morning custom, while in other cities patterns of commuter traffic and public transport are influential to a much greater extent.

1.3 Activities

1.3.1 Expenditure and Goods Bought

Earlier we saw that average expenditure amounts to £23 per consumer, to give £3.60 per visit or £5.20 per trip. Within the week expenditure is far more concentrated than other measures of activity, and heavy emphasis is given to the Thursday-Saturday period. Across time periods expenditure patterns are less concentrated: morning rates of activity are deflated and the afternoon-evening period assumes a larger role. Many travel surveys ignore these expenditure patterns and, as a result, retailers and planners have received misleading information.

Also ignored in many travel surveys is the composition of each consumer's basket of goods. Shopping might well serve a social function, but principally it is a means of satisfying household needs and, therefore, it is important to know precisely what people are buying. A comprehensive list of 68 product fields was provided on each diary sheet, and from these records a profile of people's shopping baskets has been assembled.

Table 1.6(a) lists the five most important and five least important product fields as a share of goods bought. Bread and rolls were purchased on average 1091 times per week (2.4 times per consumer) to give a 8.1% share of all purchases. Next are fresh vegetables with a 6.2% share, followed by convenience meat items (ie. cooked meats, sausages, meat pies and beefburgers), fresh fruit and biscuits. Several of these popular items are perishable and are best eaten fresh.

Lying at the bottom of the list are goods which are eaten infrequently, or preserved very easily, or regarded as luxury foods. Syrups, for instance, tend to last a long time. Prices for ground coffee and cocoa were historically high in 1982, consequently these items were seen as luxuries. None of these goods has a purchase share above 0.2%.

Finally, the size of each main group of products is laid out in table 1.6(b). Largest of the groups is that for baking and bread products (19% of all purchases). Next in overall importance are dairy produce (16%) and meats (15%). These three groups subsume most staple and protein foods. Smallest of the categories is that for spices and sauces (3%).

To compare the percent of goods bought in Cardiff against the percent of family food expenditure recorded in national surveys we remove cleaning agents from the list of items on the diary forms. Carcase meat and poultry claims 4.8% of all purchases in Cardiff, and convenience meat items and canned meats have a 8.6% share. What a comparison against national figures shows is that rates of buying do not correlate directly with levels of expenditure. Nationally 18.1% of the entire household food budget is spent on carcase meat and poultry, and 13.5% is spent on other meats (Ministry of Agriculture Food and Fisheries 1982, Insight Research 1983), both these percentages exceed the shares quoted for goods bought in Cardiff. The item most frequently recorded by members of the panel, bread/rolls/buns, represents 8.9% of all purchases, and yet in national expenditure surveys it barely amounts to 6.5% of the food budget, and is of much less importance than protein foods. Quantities bought and expenditure do not rise in unison.

A related issue is how the composition of each basket is influenced by where and when one shops. One claim is that frequently bought fresh foods are more likely to be bought locally. To investigate this issue market shares for each product are calculated across the range of store locations (city centre, district centres, etc). There are few systematic relationships between type of store location and goods bought - purchases of fresh fruit tend to be made locally, but this local bias is undramatic and exceptional. A similar conclusion is reached when day of purchase is examined.

Neither type of store location nor day of week has a marked systematic effect. By contrast, store function and organisation is associated with the purchase of specific goods. Corroboration of these results is to be found in another survey of shopping in Cardiff (Welsh Consumer Council 1982). The Welsh Consumer Council found that about 20% of consumers usually visited a superstore to buy household cleaning-agents and general groceries, whereas less than 10% used a superstore to buy meats and bread. The latter goods were more likely to be bought at corner shops or at specialist outlets. To conclude, different types of goods are bought at superstores and specialist shops; it matters little where these are located or on what day the purchase is made.

Table 1.6

Aspects of Grocery Shopping:
Average Number of Goods Bought over 24 Weeks

(a) Individual Product Fields

	Average number of goods bought	Share of all goods bought (%)
Five most important product fields:		
1 bread and rolls	1091	8.1
2 fresh vegetables	840	6.2
3 convenience meat items	572	4.2
4 fresh fruit	553	4.1
5 biscuits	540	4.0
Five least important product fields:		
64 ground coffee	24	0.2
65 baby foods	24	0.2
66 honey and syrups	20	0.1
67 frozen fruit	16	0.1
68 cocoa	13	0.1

(b) Product Categories

Ranked product categories	Size of product market relative to all goods bought (%)
1 bread and baking ingredients	19
2 dairy produce	16
3 meat products	15
4 vegetables	10
5 cleaning agents	9
6 beverages	7
7 fruit	6
8 fillings	5
9 desserts	3
10 sauses and spices	3

These categories account for over 90% of goods bought

1.3.2 Multi-Stage Grocery Shopping

Virtually 2000 trips per week are described by panellists living in Cardiff, and of these about 1400 are single isolated visits to a shop selling groceries. That is, 73% of trips are single-staged and 28% are multi-staged. The average consumer, therefore, makes 1.2 multi-stage trips each week.

Undoubtedly the majority of consumers - though by no means an overwhelming majority - are patronising just one grocery outlet when they shop. Moreover, even when several shops are visited only one or two others will be involved; ie. 62% of multi-staged trips are two-staged, and a further 27% are three-staged. A mere 3% of multi-stage trips include visits to five or more shops.

These results are summarised in table 1.7 and next to each value is the comparable figure for Watford. In the earlier survey multi-stage trips claimed a greater proportion of the total (39%), although when expressed in terms of numbers per consumer the figures look similar (1.2 trips in Cardiff and 1.5 in Watford). Slightly more four- and five-stage trips occurred in Watford; this difference arises because the Watford survey looked at a wider range of goods. Such minor discrepancies in a few entries of the table should not obscure the overall impression of similarity.

Many habits have not altered over the past decade. To see if this conclusion remains true for detailed aspects of activity, the number of stages are disaggregated for each day of the week. Absolute numbers per consumer per day are shown in table 1.8 and figure 1.2 is constructed from absolute daily totals.

Multi-stage trips per consumer are consistently below those for Watford. In both instances the proportion of trips that are multi-staged reaches a peak towards the weekend. In Watford the peak is attained on Thursday and Friday, whereas it happens one day later in Cardiff. Not only is the overall level of activity greater towards the weekend, also there are more trips with three or four stages. These features are prominent in Cardiff; for example on Friday and Saturday the average number of three-stage trips per consumer is 0.11. The complex set of linkages associated with these days is in sharp contrast to the single- and two-stage patterns which are observed from Monday to Wednesday.

Daws and McCulloch (1974,22) in their commentary for the Watford survey draw attention to the fact that the daily contribution of single-stages to all shopping trips is much lower on weekdays (almost 55%) than at weekends (74% on Saturday). This pattern is not easily explained because one would expect the removal of time constraints on Saturday to reduce the proportion of single-stage trips. By contrast, daily contributions in Cardiff are as expected: single-stage trips claim about 75% of the total from Monday to Thursday, and on Friday and Saturday the percentage falls below 70%. Only Sunday is dominated by single-stage trips.

Many of the multi-stage trips on Friday and Saturday are destined for larger shopping centres and are in the nature of family outings. Time constraints are less important and discretionary aspects of movement come to the fore, such that consumers are

Table 1.7

Aspects of Grocery Shopping:
Average Number of Shopping Trips per Week

Comparison of Cardiff and Watford Consumer Panels

	Average number of trips per week		Average number of trips per consumer per week		Percent of all trips	
	C	W	C	W	C	W
Trips:						
Single-stage	1434	3985	3.2	2.4	73	61
Multi-stage	545	2514	1.2	1.5	28	39
All	1979	6499	4.4	3.9	100	100
Composition of multi-stage trips:						
Two-stage	338	1380	0.8	0.8	62	55
Three-stage	146	662	0.3	0.4	27	26
Four-stage	46	260	0.1	0.2	8	10
Five or more	15	213	0.0	0.1	3	9
Sub-totals	545	2514	1.2	1.5	100	100
Consumers in samples	451	1672				

C Cardiff panel 1982 24 weeks
W Watford panel 1969 1 week
(Adapted from Daws and McCulloch 1974, table 5)

Table 1.8

Aspects of Grocery Shopping:
Average Number of Shopping Trips per Day

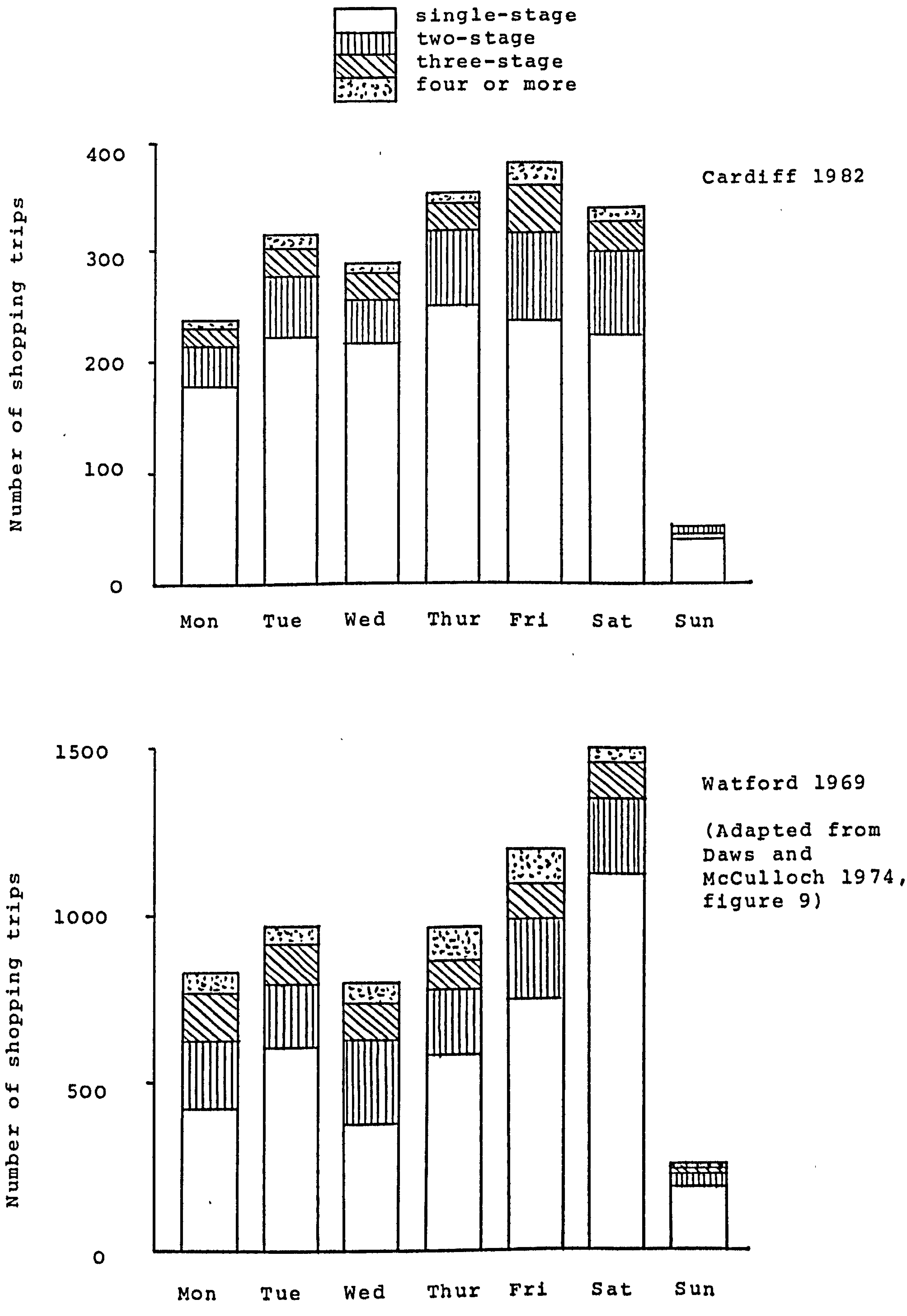
Comparison of Cardiff and Watford Consumer Panels

		Average Number of Shopping Trips per Consumer per Day						
		Mon	Tue	Wed	Thur	Fri	Sat	Sun
Trips:								
Single-stage	C	.43	.51	.50	.60	.60	.54	.15
	W	.27	.34	.26	.32	.43	.67	.10
Multi-stage	C	.12	.22	.16	.22	.27	.27	.00
	W	.23	.24	.21	.26	.30	.23	.03
All	C	.55	.72	.67	.83	.87	.81	.15
	W	.50	.58	.47	.58	.73	.90	.14
Composition of multi-stages:								
Two-stages	C	.08	.14	.11	.15	.16	.15	.00
	W	.12	.14	.11	.12	.17	.15	.02
Three-stages	C	.03	.06	.04	.05	.08	.08	.00
	W	.07	.07	.06	.07	.06	.05	.01
Four or more	C	.01	.02	.01	.02	.03	.04	.00
	W	.04	.04	.04	.06	.07	.02	.01

C Cardiff panel 1982 24 weeks
W Watford panel 1969 1 week
(Adapted from Daws and McCulloch 1974, table 6)

Figure 1.2

Aspects of Grocery Shopping:
Average Number of Shopping Trips per Day



prepared to search among different shops for bargains or better quality goods.

1.3.3 Multi-Purpose Grocery Shopping

Journeys may originate from many places and these may be linked together to form a sequence of multi-purpose activities called trip chains. The identification of trip chains is associated with the notion that people schedule their activities and movements. All manner of nodes may be in this sequence, including the homes of friends, squash courts and bingo clubs. Normally, where shopping is the principal purpose of travel, the range of origins and destinations is quite narrow: the home, workplace and other shops. Also, other aspects of family maintenance are linked with travel for grocery shopping, such as collecting children from school and buying clothes for members of the family.

The main features of multi-purpose travel are shown in table 1.9(a) Conventional spatial interaction models often treat the home as the source of all trips, whereas we discover that only 68% of trips originate from the home. Workplaces are the origin for 12% of trips, which is a high percentage given that only 45% of the sample actually work outside the home. The remainder of trips come under the heading of family maintenance tasks, some of which involve visits to other shops (selling clothes, durables and personal services). Finally it is possible to purchase goods without moving from home. Mobile traders, mail order companies and hawkers all deliver straight to the consumer's house and 3.5% of 'trips' are of this form.

For most aspects of multi-purpose travel similar proportions are observed irrespective of whether trips, expenditure or goods are measured. The only difference is that when expenditure is measured home-based travel tends to be slightly more important and suppliers play a smaller role.

Averages for each type of origin may be disaggregated by day and time, and a few examples are presented in part (b) of table 1.9. The distribution of home-based trips describes a steady rise throughout the week to reach 20% on Saturday; this compares with only 4% of work-based trips on the same day. Given the decline in Saturday morning work, except in the retail and personal service sectors, these contrasts on Saturday are to be expected.

The distribution of types of origin across time periods reveals a number of interesting features. Of all home-based trips, 45% are concentrated into mid-morning (10 am to noon) and the only other significant time slot is mid-afternoon (2 pm to 4 pm). This contrasts with work-based trips where 43% happen over lunch (noon to 2 pm) and a secondary peak is observed on the journey home from work (4 pm to 6 pm).

Two-way classifications of origins by day and time reinforce the patterns noted already. When home is the origin the single most important period is 10 am - noon on Saturday (9.4% of all home based trips), while the equivalent for workplace origins is noon - 2 pm on Thursday (10.6% of all work-based trips). In all cases rates of activity before 10 am and after 6 pm are relatively unimportant.

Table 1.9

Aspects of Grocery Shopping:
Origins of Shopping Trips

(a) Summary Features

Origins	Percent of shopping trips	Percent of expenditure	Percent of goods bought
Home	68	74	75
Workplace	12	10	10
Other place	9	7	7
Other shop	8	7	6
Supplier	4	2	1
	100	100	100

'Other place' includes schools, hairdressers, etc.

(b) Days and Times

Origin	Trips per Day of Week (%)							
	Mon	Tues	Wed	Thur	Fri	Sat	Sun	Total
Home	12	15	14	17	18	20	3	100
Workplace	15	20	17	24	20	4	0	100

Origin	Trips per Time of Day (%)						
	Before 10am	10am Noon	Noon 2pm	2pm 4pm	4pm 6pm	After 6pm	
Home	11	45	14	21	6	3	100
Workplace	1	11	43	19	25	1	100

Because definitions are not the same in the Watford survey it is not possible to draw any direct comparisons. However, it is worth noting that where the journey was multi-purpose the most frequent combination took the form: work-shop-home. The distribution of work-based trips across the week is almost identical to that observed for Cardiff: over 20% on Thursday and Friday, about 4-5% on Saturday, and between 15-19% from Monday to Wednesday (Daws and McCulloch 1974,25).

Greater recognition is being given to the role of multi-stage and multi-purpose trips. Much of this interest has arisen because of dissatisfaction with models which assume all trips to be of the home-shop-home variety. Failure to appreciate the subtleties of multi-link chains can lead to the mis-specification of: (i) aggregate spatial interaction models (O'Kelly 1983,b) and (ii) activity / discrete choice models (Adler and Ben-Akiva 1979, Burnett and Hanson 1979). Some implications for modelling are explored in the context of the Watford panel by Bentley et al. (1977).

2 Aspects of Grocery Shopping: Family and Work

This is the first of two sections designed to explore how behaviour is influenced by the personal circumstances of consumers. Rather than attempt to cover all possible influences attention is focussed on family and work, and aspects of space and mobility. Emphasised in the first of these sections are temporal patterns and social constraints. In the second section forms of travel, access, distance and the location of destinations are studied. These particular topics are selected because of their relevance to the study of shopping choice and movement; furthermore, they provide a descriptive and normative backdrop for the models presented in part II of the thesis.

2.1 Family and Work

Like travel, grocery shopping is a derived demand. As a derived demand it is done to satisfy both personal and family needs. For this reason it is important to look beyond the aggregate counts and to consider the context in which shopping is undertaken.

At least three aspects are noteworthy. First, any activity can be seen as a resource. If the person works then the 'consumption' of shopping trips is squeezed into a narrow interval of time during the lunch-hour or en route from the workplace. Alternatively, if shopping relieves the boredom and tedium and loneliness of suburban living then it is possible that extra trips are 'consumed'.

Secondly, the pattern of trip-making will vary between families because of differing expectations and because of role-based divisions of responsibility. The formation of these roles is a social process that has a bearing upon all aspects of family life, from child-rearing to leisure. Social processes reinforce many established roles; they also provide the dynamic to alter divisions of personal responsibility. The rising importance of shared shopping trips is one illustration of how patterns of behaviour mirror changes within the home.

Finally, the act of doing shopping means that the possibility of doing something else is foregone. A visit to the corner shop, therefore, will include the cost of goods bought (unless the person is browsing) plus the cost of lost opportunities (such as not participating in paid labour or not walking in the park). The quality and efficiency of life are directly affected by such costs.

In the following sub-sections a detailed study is made of these three aspects of family structure and life-style. Special attention is given to the influence of work outside the home and to the notion of familism. It is helpful to keep in mind the following definitions:

(1) Working types

Personal behaviour is shaped by the working status of each consumer. Whether a shopper is engaged in household tasks or paid labour will determine the allocation of time between competing projects and influence the scope for discretionary behaviour. Women members of the Cardiff panel are divided into those who are employed full-time (more than 30 hours per week), those employed part-time (less than 30 hours per week) and all others (housewives, the retired and so on). All male shoppers are collected together in a separate category.

The conventional categories that are used here need to be treated carefully; for many women, full-time paid employment is complemented by a full ('informal') schedule of housework. Leisure is of secondary importance and the amount of discretion is limited by responsibilities towards both job and family.

(2) Family types

Urban populations are commonly segregated on grounds of age differences, position in the life-cycle, type of household, and life-style. These features have a bearing on the relative ease of travel and carriage of goods, and on the capacity to combine shopping functions with other activities such as child-rearing and visits to friends.

The Cardiff panel members are divided into 8 family segments which are similar to those adopted in the General Household Survey. These definitions are modified in order to give a more sensitive account of women's movements (ie. the number of young children and the level of child-benefit are directly relevant whereas the occupation of the head of household or gross household income are indirect influences).

The discussion of working types and family types is illustrated with tables and graphs, these show weekly averages calculated from data collected over five weeks (February 8 to March 14, 1982). The five week period is regarded as sufficiently long for the main themes to be identified. Weekly, daily and diurnal features are described for all the segments outlined above.

2.2 <u>The Frequency of Grocery Shopping</u>

2.2.1 Weekly Rates

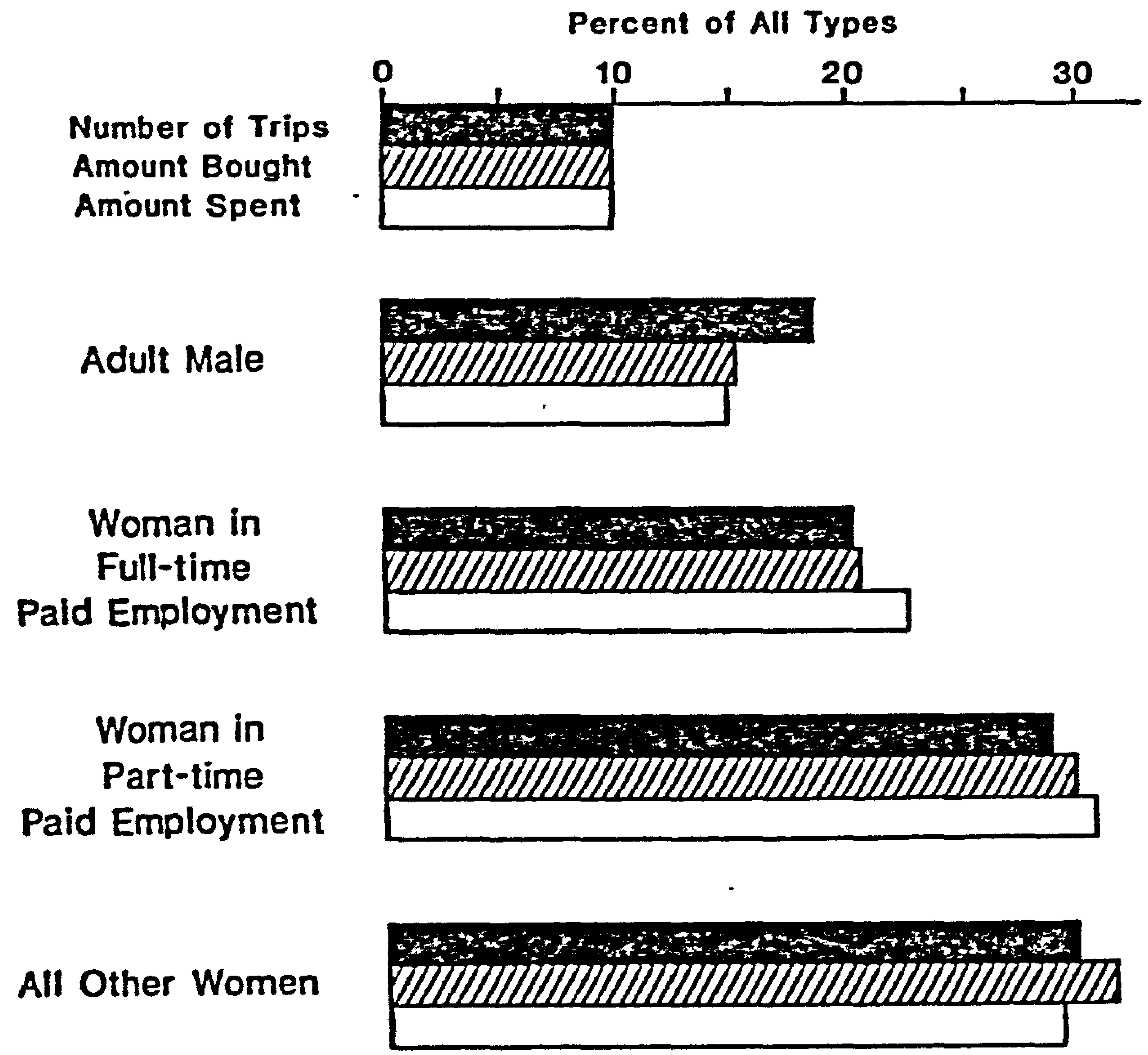
(a) Working types

The three largest segments refer to women alone. Those who are in full-time paid employment comprise 13% of panel members. Part-time workers and female students form a further 30% and the remaining panellists are mainly women who fulfil the traditional role of a housewife.

Those who maintain a full-time job fall well behind other groups of women in terms of shopping activity. Their activity rate is about 4.3 grocery trips per week which compares with 6 grocery trips per week among all other women. Expressed another way, full-time female workers take a 22% share of all trips, and each of the other groups of women have a 30% share (figure 2.1).

Figure 2.1

Selected Measures of Shopping Trips : Working Types



	Items per Trip (No.)	Expenditure per Trip (£)	Expenditure per Item (Pence)	Shopping Trips (No.)
Adult Male	5.7	3.69	72	4.0
Woman in Full-time Paid Employment	6.3	5.36	85	4.3
Woman in Part-time Paid Employment	6.6	5.08	77	5.9
All Other Women	6.7	4.57	69	6.2

Women who work full-time spend £5.36 per trip, a figure which is higher than for all other groups. Their expenditure on each item is higher too. The operation of time constraints is signalled by these levels of expenditure: the absolute number of trips is minimised by concentrating expenditure into as few occasions as possible. In addition, their higher disposable income allows them to buy luxury items, this may explain why women working full-time spend 85 pence on each item when all other women spend 69 pence.

Shopping most frequently, with an average of over 6 trips each week, are housewives. Many have the added responsibility of childcare, although generally housewives have more time to make numerous short visits and a greater opportunity to combine shopping with visits to friends, meeting neighbours and servicing other family needs. In short, the economic value of time is less obvious.

Corroborative evidence for these rates of activity is contained in the National Travel Survey (Department of Transport 1983). The Survey shows that only 26% of journeys made by women working full-time are for shopping and personal business purposes, whereas the equivalent figure for housewives is 55%. Earlier studies confirm the pressure of time on working women (who continue to do domestic work). Diary evidence from Watford shows how 4.5 shopping journeys per part-time worker falls to 1.8 journeys for full-time workers (Daws and McCulloch 1974,52).

The last group comprises male panellists alone. There are differences between men who work full-time (often young singles) and the retired (whose range of movement is restricted by walking problems and arthritic complaints). Unfortunately numbers on the Cardiff panel are small (28 men altogether) and it is impractical to obtain meaningful sub-samples. Nevertheless for all these men we expect shopping to be infrequent and spatially bounded. With less than 4 trips each week support is leant to the belief that young men have limited time available and lack the inclination to shop (ie. they do not recognise any social benefit), while the elderly suffer from imposed immobility.

Two qualifications need to be made before proceeding any further. First, there are notable variations in the spread of sample frequencies. Thus, men are light trip-makers of whom 63% register 4 or less trips, yet almost 4% record 10 or more trips. Every group is characterised by a range of trip rates, which implies that group averages are crude measures of activity.

Second of the qualifications makes reference to household size. Small size is the main reason why expenditure per trip is no more than £4 in male households. Women who are in part-time paid employment or who do not work tend to manage larger households, and this gives rise to an average purchase of 40 grocery goods each week - a figure 50% above men's purchasing rates. Attention is turned, then, to consider household composition and household size.

(b) Family types

Selected weekly averages for 8 family types are given in figure 2.2. Bar graphs show how three measures of activity are distributed among the different family types, and against each of these are the number of goods bought and levels of expenditure.

In discussion of these family types a distinction is drawn between singles, small households and large households.

(i) Singles

Single women aged 16 to 59 make fewest trips each week (4.8 trips per week). Low levels of trip-making are also evident among single elderly women. Both groups record low average expenditures and low expenditures per item. Possibly this arises from insufficient disposable income and from thriftiness. For males (another group predominantly living alone) higher rates of expenditure suggest that the search for bargains and price sensitivity are less important. All three groups participate in fewer trips than women in married families, absolute household size being a controlling factor. In addition, young singles often have a negative attitude to shopping (since it rivals time spent on leisure and recreation pursuits), and the elderly are impeded by ailments and infirmity.

(ii) Small households

At an aggregate level small adult households (2 persons aged 16 to 59) and small nuclear families (adults with 1 and 2 children) share several common features. The average number of trips lies in the range 6 to 6.5 per week and slight variations in expenditure are ascribed to differences in household size (ie. the presence of children in nuclear families). For many panellists in these households time resources are limited: many adults work, leisure pursuits are important, and often much time is given to childcare.

Those households with two adults aged 60 or more define a third small adult household. Although sizes are similar in all three groups shopping may be less easy for the elderly; often they are less mobile, and have a lower disposable income, than those aged 25 to 59. Also, patterns of shopping among elderly people might be more sensitive to inclement weather.

(iii) Large households

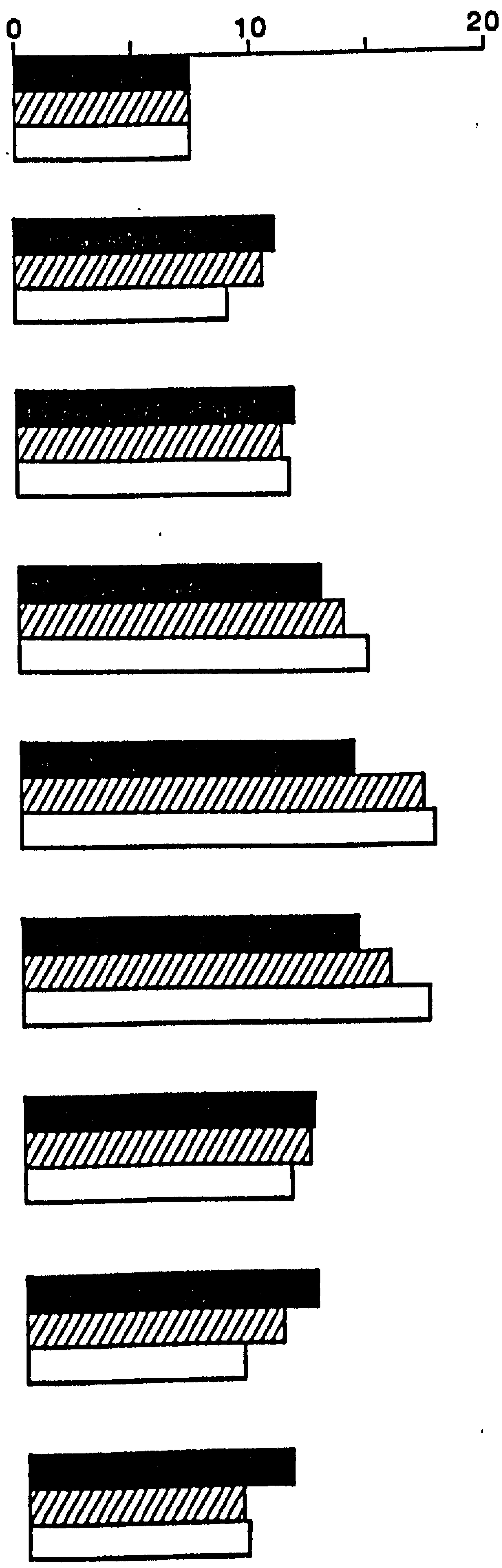
Mainly because of the numbers in each household more trips are undertaken by women in large families (3 or more children) and in large adult households (3 adults). About 6.5 trips are made by these women and on each occasion approximately 7 items are bought at a cost of over £5.

Bulk buying by members of large households is not correlated with a much lower spend per item. Nor do shoppers reduce their rate of activity in an attempt to raise household efficiency. It is possible that without access to a car the number of goods which can be bought, and therefore the scope for bulk-purchase economies, is severely limited by carriage constraints and distance from home.

Shopping activity is inextricably linked with household size and family formation. Marriage and the birth of children will increase the frequency of these trips. This conclusion is an exact echo of

Figure 2.2

Selected Measures of Shopping Trips : Family Types



	Items per Trip (No.)	Expenditure per Trip (£)	Expenditure per Item (Pence)	Shopping Trips (No.)
Single Woman 16 - 59	5.9	3.68	62	4.8
Small Adult Household	5.9	4.17	70	5.4
Small Family	6.7	4.88	73	5.8
Large Family	7.4	5.16	70	6.5
Large Adult Household	6.8	5.16	76	6.5
Small Elderly Household	6.1	3.83	63	5.7
Single Woman 60 or More	5.5	3.11	57	5.7
Male Household	5.2	3.56	69	5.1

earlier evidence from Watford (Daws and McCulloch 1974) and from Uppsala (Hanson and Hanson 1980).

2.2.2 Daily Rates

Shown in figure 2.3 are daily variations in trip frequency. This diagram is constructed in such a way that the daily contribution of trips is emphasised. Daily trip numbers are expressed as deviations from the weekly average (based on a norm of 100 per day). Generally shopping on Monday to Wednesday is light and does not depart from the norm. Over the period Thursday to Friday there is a marked surfeit of trips, while a dramatic deficit is recorded on Sunday.

Turning to work types first (figure 2.3(a)), a striking contrast is observed between women in full-time employment and all other groups. For full-time working women, average daily volumes almost reach 150% on Friday and Saturday, whereas they are at a nadir on Monday and Wednesday. In a sense these dual workers 'catch-up' on shopping at weekends and this implies that overtime earnings are foregone or leisure is lost.

Women working part-time do not differ in any significant respect from those without paid work. The opportunity exists to shop on many occasions within the bounds imposed by opening hours. Saturday is less popular and there is a tendency to stock goods for the weekend by shopping heavily on Friday. The distribution of activity may indicate a low valuation of time or a desire to fill unoccupied periods with productive consumption.

Comparison of the daily profiles for family types (figure 2.3 (b)) shows that there is no single peak. Saturday is of primary importance for small households (single males, single elderly women, and small adult households) while Friday is the peak for nuclear families. Indeed, the concentration of shopping into Friday by large adult households - representing virtually 140% of the daily average - suggests that activity is consciously scheduled so that household tasks might be shared among family members.

These peaks are punctuated by a couple of troughs on Monday and Wednesday. Monday is traditionally unpopular among all groups of consumer: new deliveries have yet to reach shops, household food stocks are not yet depleted, superstores often close and other tasks take precedence (especially washing and cleaning). The low level of activity on Wednesday arises because of early closing by many small traders.

2.2.3 Diurnal Rates

The typical diurnal profile rises during the morning, passes through a lunchtime lull, goes on to an afternoon recovery and ends at an evening low. These features are observed for most segments of the panel and hold true whether one measures absolute trips, or items bought, or expenditure. One aspect of shoppers' circumstances that does give rise to differences is work status.

Figure 2.3 (a)

Daily Variation in the Number of Shopping Trips : Working Types

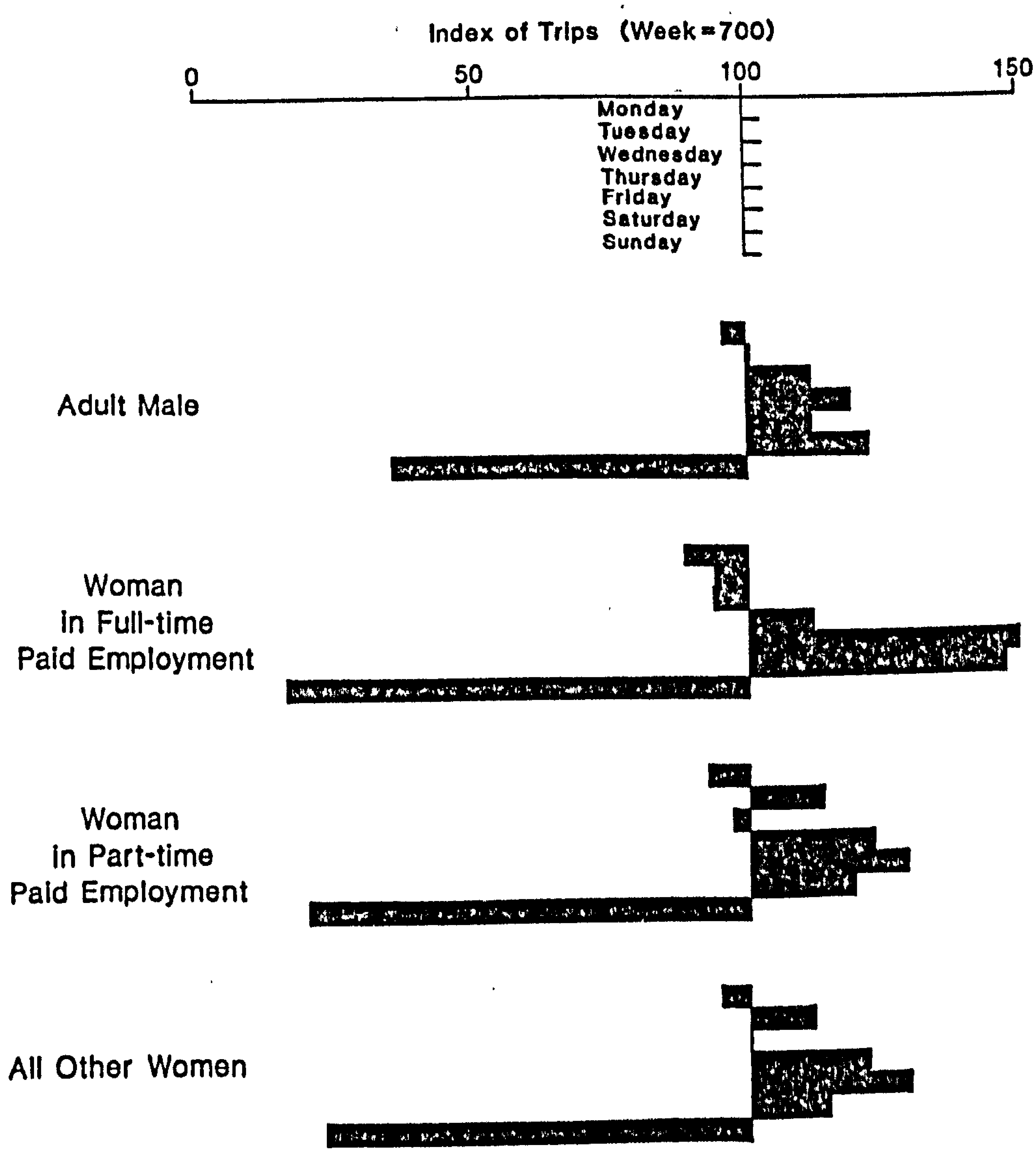
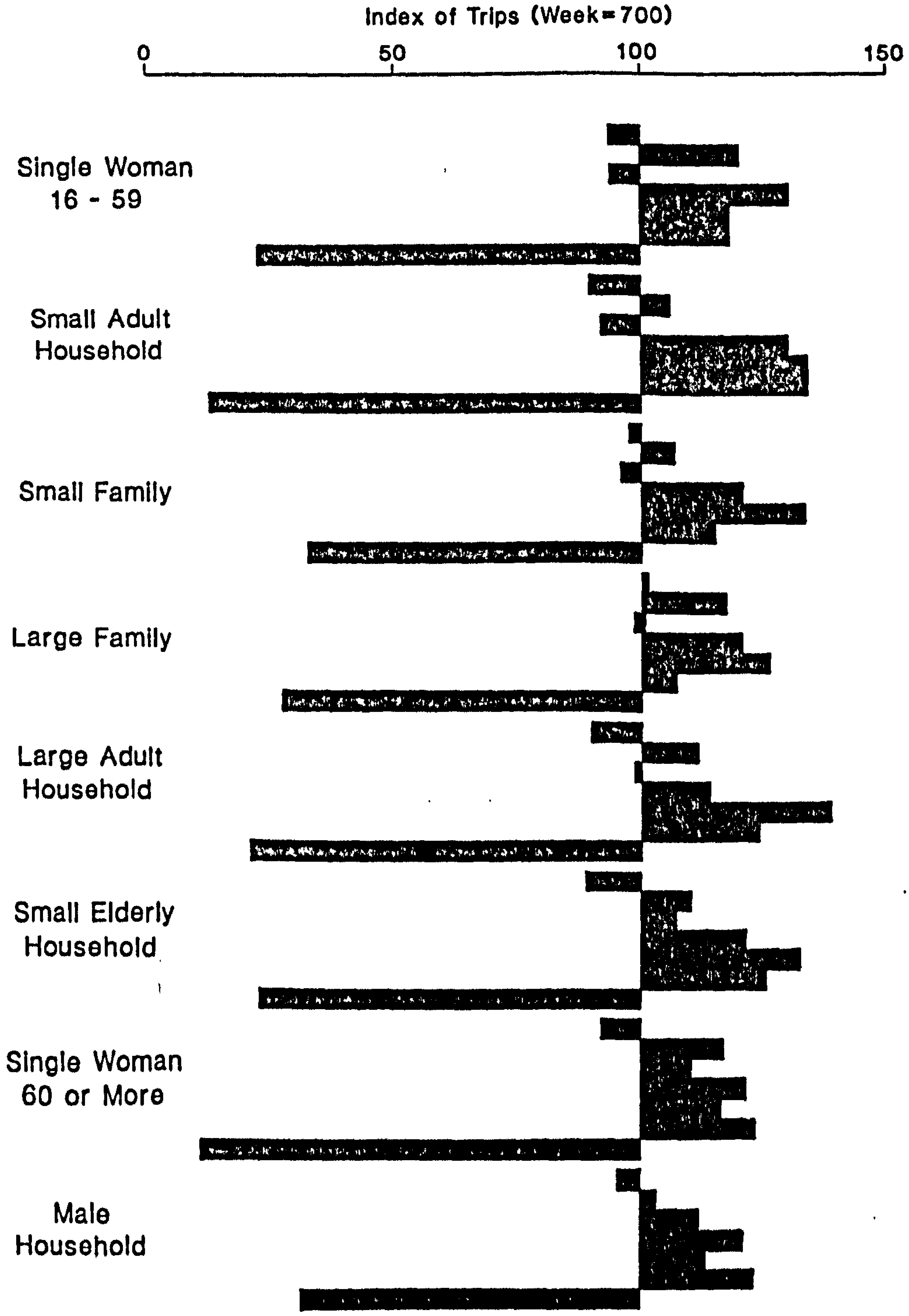


Figure 2.3 (b)

Daily Variation in the Number of Shopping Trips : Family Types



In figures 2.4 and 2.5 levels of expenditure are used to sketch profiles of activity. (Note that numbers are adjusted to correct for varying sample sizes.)

A significant distinction is drawn between women working full-time and all others. Workers spend proportionately less money during the morning, and compensate for this deficit by spending more from 2 pm to 4 pm. Purchasing after 4 pm is definitely more significant for full-time workers, especially when compared against housewives.

These profiles have implications for statements made about people's use of time. A substantial morning peak among housewives must be seen as a response to childcare tasks. The tendency to combine frequent shopping and family maintenance is regulated by the problem of keeping control of babies and pushing prams when buying goods. Certainly if shops can be visited while youngsters are at playgroup, crèche or nursery school the problems become less acute (Tivers 1982).

The lunchtime lull is linked with the expectation that women fulfil other household tasks, specifically the preparation of meals. The dip from noon to 2 pm is least pronounced among women who work full-time. Presumably the latter group do not have to prepare family meals at lunchtime and take advantage of the spare time to shop (in fact over 5% of all shopping trips are work-based and happen at lunchtime). Also, shops near workplaces tend to stay open throughout this period, whereas many suburban shops close for lunch.

Interaction between day and time is portrayed in figure 2.5. Look at the plot for all other women ('housewives'), the dominant morning peak is repeatedly seen each day and a secondary afternoon peak is usually observed (Wednesday and Saturday being exceptions). Many part-time workers display a less regular pattern which arises because hours of work are variable. Concentrated into Thursday and Friday afternoon, and Saturday morning, are shopping peaks for full-time working women. At these times other members of the family may be available to share tasks or the family car may be available.

Daily and diurnal variation was investigated by Bullock et al. (1974) in their diary survey of Reading and similar conclusions were reached. Non-working women spent an average of 0.61 hours per day on shopping, this fell to 0.45 hours among working women. In terms of temporal variation, the peak period for housewives was 10 am to 11 am, while an afternoon peak was observed for workers. Bentley et al. (1977) provide additional evidence to link temporal patterns with escort journeys (taking children to school in the morning) and journeys home from work. Again, these earlier findings are mirrored by the Cardiff data.

2.3 Discussion

Personal circumstances have been shown to affect patterns of activity. Several implications are to be drawn which relate the situation in Cardiff to other places. Firstly, it has been demonstrated how working women economise on time by changing

Figure 2.4

Time of Day Profile : Working Types

Mean Expenditure per Individual (£1982)

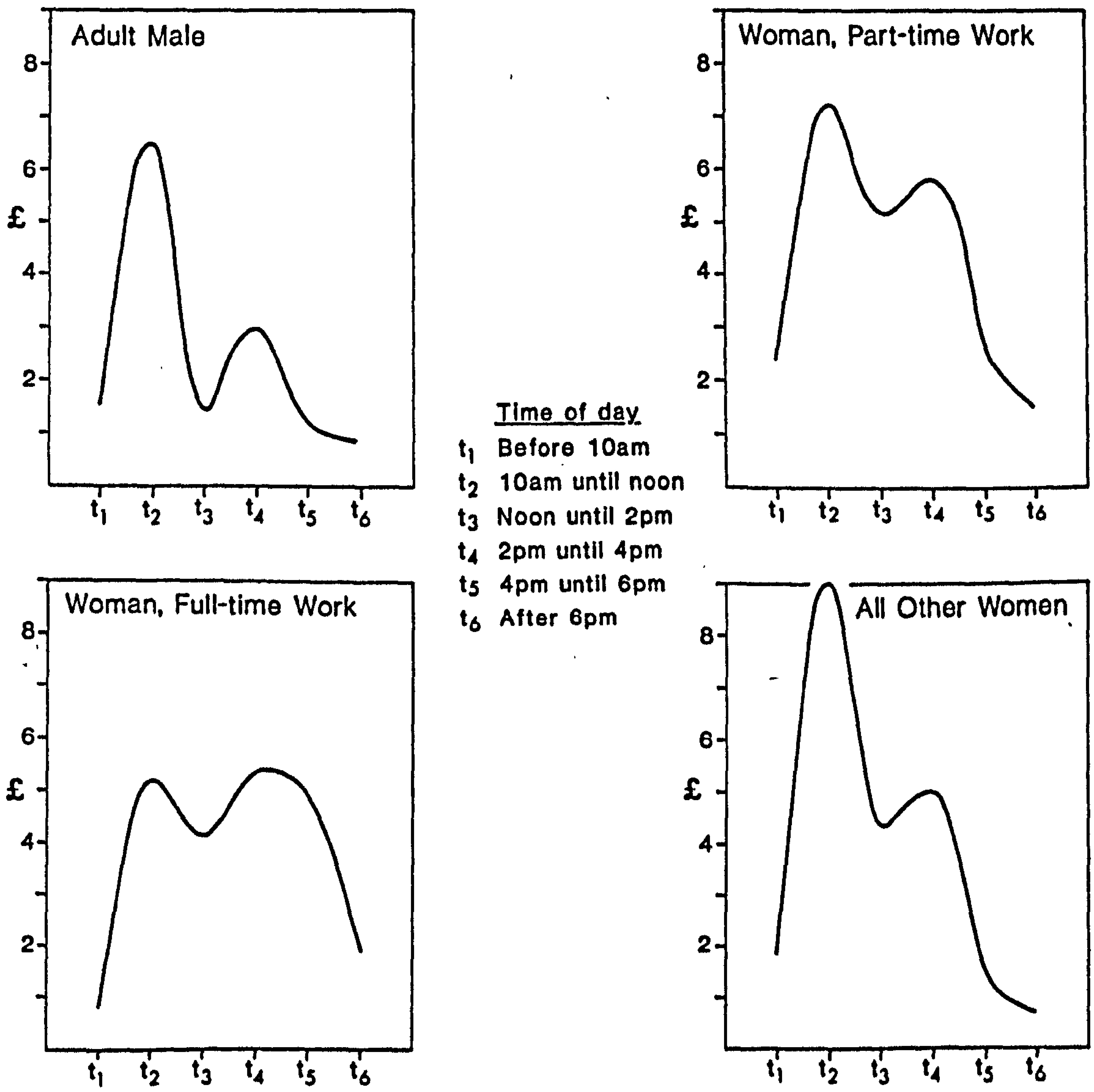
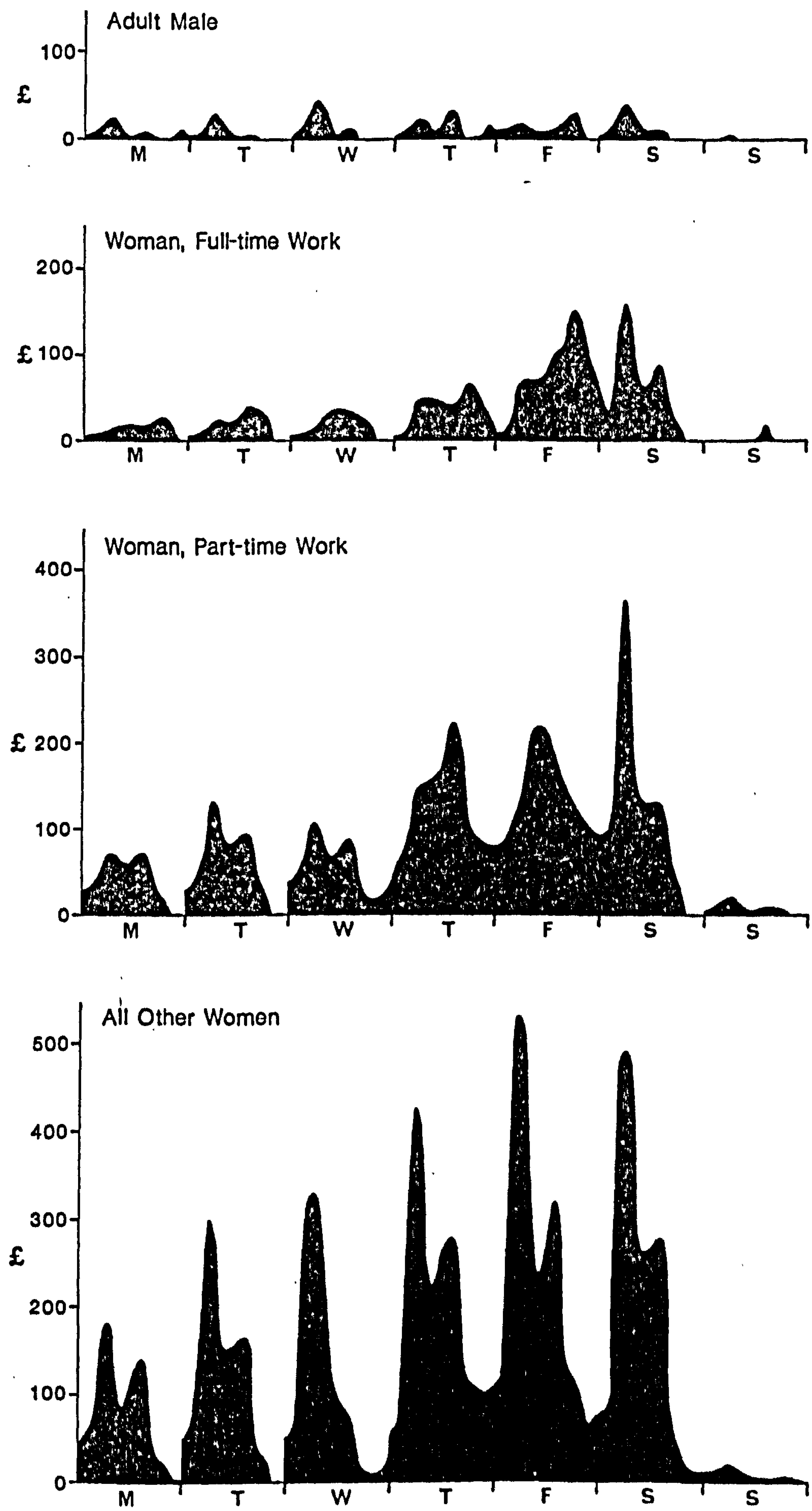


Figure 2.5 Time of Day Profile : Working Types
Mean Expenditure (All Individuals) (£1982)



Each day has six divisions
1 Before 10am, 2 10am until noon, 3 Noon until 2pm,
4 2pm until 4pm, 5 4pm until 6pm, 6 After 6pm

their non-work activity patterns and by deferring some travel to weekends. In contrast, part-time workers do not experience the same temporal pressures and their behaviour differs little from housewives. Both these aspects have been found in cultural settings which range from the United States to Sweden (Hanson and Hanson 1980).

Secondly, housewives with young children need to plan carefully their schedule of activity. All out-of-home activities must be organised with respect to escorting children and child-minding. The relationship between specific forms of shopping activity, the role of women, and rising numbers of children is strong and has changed remarkably little in recent years. Daws and McCulloch (1974) observed this relationship in Watford and Tivers (1982) in her time-space study of young mothers living in Merton has commented upon the persistence of conventional roles and traditional behavioural responses.

Finally, some support is found for Pred's (1981) assertion that productive consumption (home-making, shopping, meal preparation) can be just as rigid and circumscribed as conditions that face waged workers. In effect the work-discipline extends to all members of the family and all people are obliged to work within tight temporal and spatial constraints.

Apart from the empirical material gleaned from Cardiff and elsewhere there are two important theoretical strands which should offer additional insights in the future. One highly innovative angle is due to Becker (1981) who upholds a time-budget approach for the investigation of: (a) the efficient organisation of scarce time, and (b) ways in which time is allocated between household tasks, employment, leisure and recreation. Analysis of shopping, for instance, involves the valuation of waiting time and travel time and the opportunity cost of not doing something else. Every member of the family has a different valuation of these costs, so roles and activity patterns vary. The danger of an avowedly economic, utility maximising approach is that existing (inequitable) arrangements are justified in terms of an efficient household division of labour.

Very different is the sociological approach. Consumer behaviour is placed within the framework of family roles. Behaviour is shaped by the need to maintain family commitments, the expectations of others in the family, notions of domesticity and attitudinal norms. Geographers who have adopted the sociological approach have revealed how 'satisfaction with life' is affected by the ease with which shopping tasks can be performed. Raised are issues concerning personal access and mobility, and transport and retail provision (Tivers 1982, Bowlby 1979, 1984a, 1984b). The next section begins to provide some empirical understanding of these issues.

3 Aspects of Grocery Shopping: Mobility

In this section the themes of mobility and distance are explored. There are two sub-sections, the first deals with modal split and the second refers to distances and destinations.

Form of travel is an important influence upon patterns of consumer behaviour. Many shoppers are comparatively immobile, this situation arises because the person responsible for shopping lacks access to the family car or does not possess a driving licence. Where a car is unavailable the range of opportunities is limited and greater reliance is placed on short-distance walks and public transport. Choice of mode also depends on the type of home area, social class and material wealth, and the nature of journeys (is shopping the sole purpose or is it combined with another activity?).

Distances travelled to shopping destinations depend on travel mode and the frequency of visits. Access to a car will widen the 'activity space' and where this enables large stores to be reached the frequency of visits will fall. Flows into district centres and the city centre are influenced by absolute distance, important too is the social composition of residential areas, transport provision, and the number of retail opportunities that are available locally.

3.1 Modal Split and Shopping Trips

3.1.1 Mode and Access to Private Transport

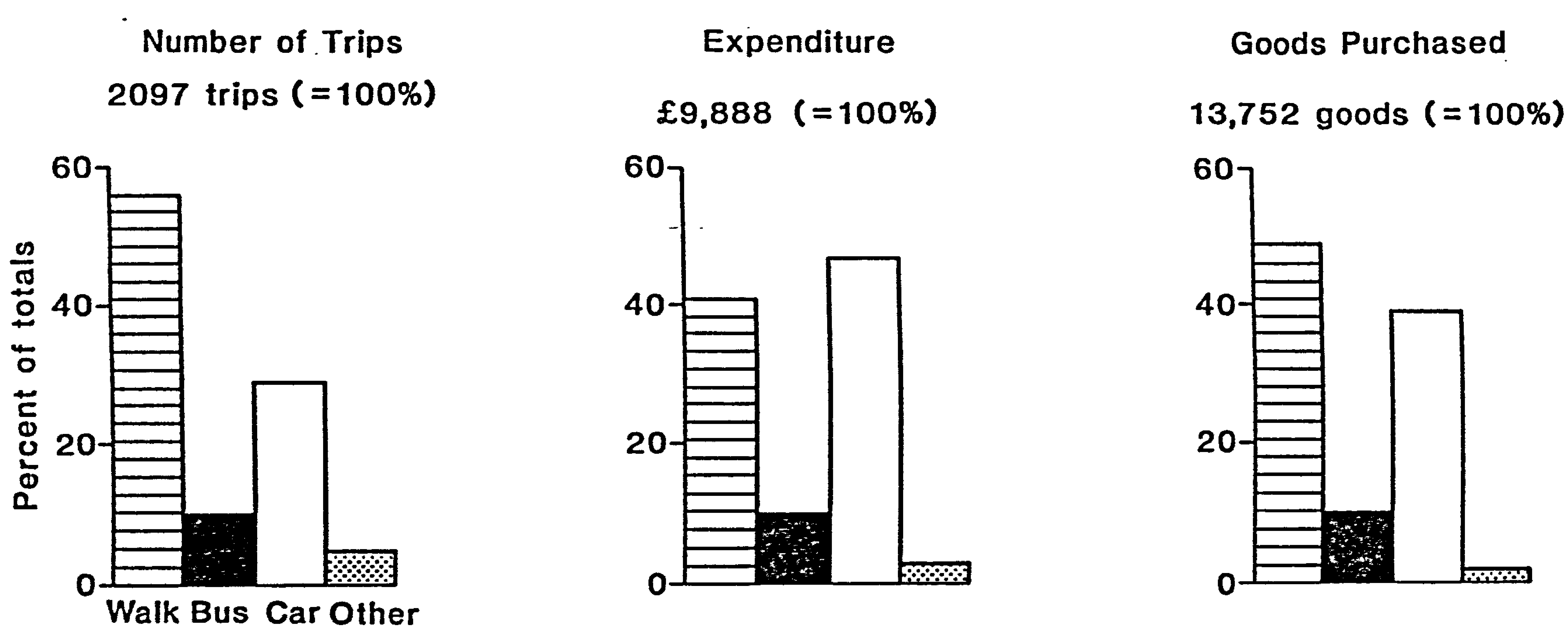
Over a five week period the total number of shopping trips is calculated and in all the tables and graphs that follow these totals are re-expressed as weekly averages. Several forms of travel are available; including walk, bus/coach, car, train, other (mainly bicycle, moped and motorbike) and a category for no travel (used when a mobile trader calls). Most of the discussion is confined to walk, bus and car since other forms of travel account for no more than 5% of movement.

Walks and car travel are the principal forms of movement (figure 3.1). Their relative importance alters as different features of shopping are measured; thus walks are dominant when the absolute number of trips is counted (56% of all trips), and car travel dominates when expenditure is measured (47% of all consumer spending). The percent of consumers who use buses remains constant at about 10-14% of all travel. This translates into 200 bus-borne trips each week and involves the purchase of about 1,500 grocery goods.

Data from the 1978/79 National Travel Survey shows that modal split in Cardiff is typical of the whole nation. Some 46% of shopping journeys over 50 yards are by foot, 13% by local bus and 36% by car (Department of Transport 1983). Quite how these proportions have changed over recent decades is hard to establish

Figure 3.1

FEATURES OF SHOPPING TRIPS : DIFFERENT MODES (PER WEEK)



because earlier surveys often excluded pedestrian travel. Comparison with data from Watford (Daws and McCulloch 1974) indicates that usage of public transport may have declined slightly and that this has been reallocated to car travel. Pedestrian movement appears to be as important today as it was thirteen years before. For instance the Watford figure of 58% of journeys by foot on Monday and Tuesday is replicated in Cardiff.

Underlying these overall levels of modal split are several factors. Access to private transport is the decisive influence. Three measures of access are defined from the Cardiff data: (a) percent of the panel who hold a current driving licence, (b) percent living in households without a car, and (c) percent who never, or only sometimes, have use of a car.

The number of consumers who hold a current driving licence defines the upper limit of those who can independently travel by car. The figure is 36% amongst panel members. This upper limit should be compared against the figure of 70% which is the proportion of households with a car. Often travel surveys report the latter figure alone and misleading conclusions are drawn.

The danger of placing too much reliance on household measures (rather than personal ones) is evinced when we note that 70% of consumers in Cardiff said that they never, or only sometimes, have use of a car. The family might possess a car, but quite likely it is unavailable to several members.

Taking the three measures of access together, at least one third to one half of consumers do not have access to private transport. As a consequence we might expect heavier use to be made of public transport. Plotted in figure 3.2 are levels of modal split among people without a car, these are expressed as percentage deviations from the weekly mean. For instance, pedestrian travel is up to 19% greater among those without use of a car and bus travel is up to 6% greater. Absence of private vehicles is compensated by walks rather than public transport.

Car travel falls to about 24% of the mean in figure 3.2. It does not disappear altogether because shoppers are chauffeured by friends, neighbours and spouses. Nationally some 16% of all shopping and personal business journeys are undertaken as car passengers.

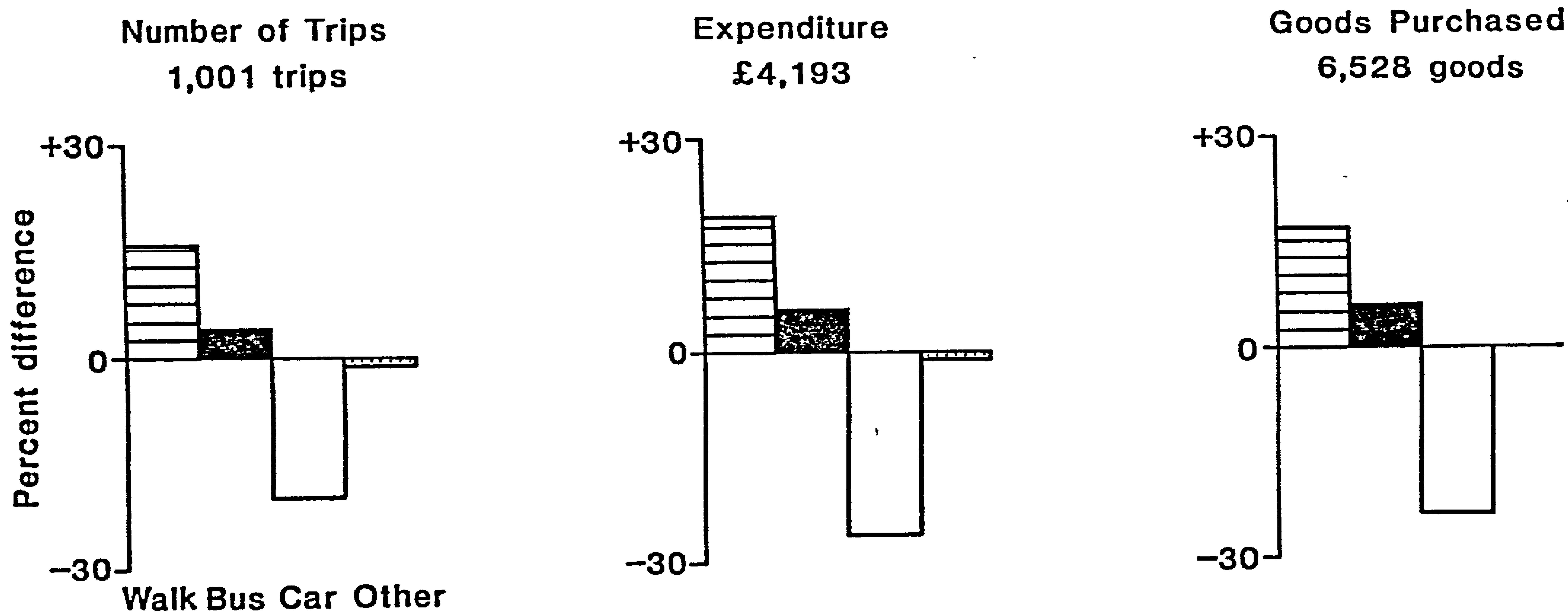
Further differences in travel opportunity are revealed if attention is given to bus journeys. A graph of the daily distribution of bus trips (figure 3.3) shows that patronage across days is fairly steady (except Sunday). The major variation is between the mid-morning peak (10 am to noon) and all other times. Rarely are bus trips observed during the early evening.

The level of car availability is used to disaggregate trips. This confirms that where a car is always available buses are hardly ever ridden (the flexibility of movement by car outweighs the cost of petrol/parking and the inconvenience of negotiating congested streets). More interesting are the differences which occur when a car is sometimes available. Bus trips are concentrated into the period Monday to Wednesday; at other times this group

Figure 3.2

FEATURES OF SHOPPING TRIPS : DIFFERENT MODES CHOSEN BY SHOPPERS WITHOUT USE OF A CAR (PER WEEK)

(A positive percent difference shows that those without the use of a car choose the associated mode more often than is true for all shoppers)



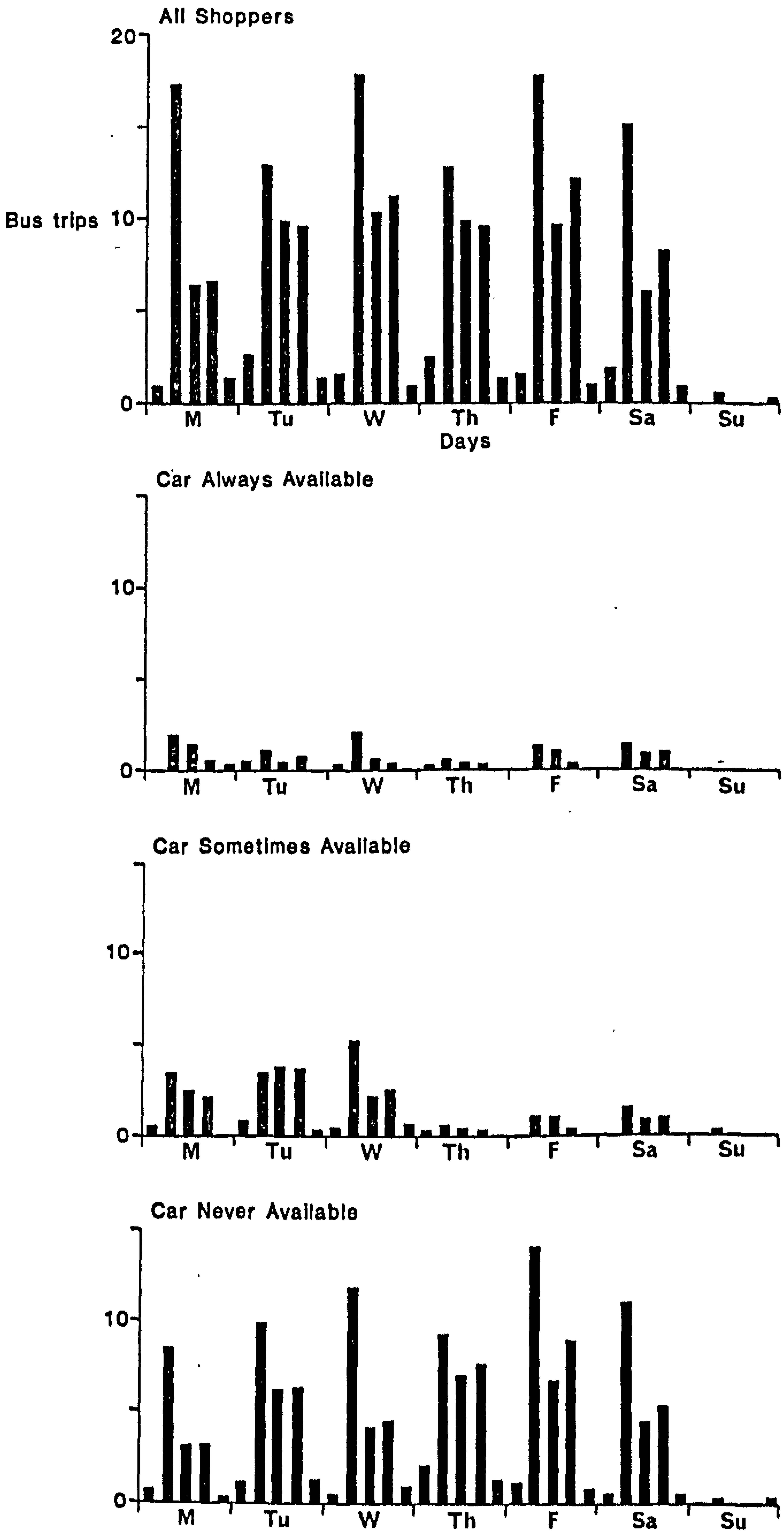


Figure 3.3

TIME OF DAY PROFILE :

MEAN NUMBER OF SHOPPING TRIPS USING A BUS (PER WEEK)

Each day has five divisions :

1 Before 10am
2 10am until Noon
3 Noon until 2pm
4 2pm until 4pm
5 After 4pm

behaves just like those who always have a car. Where possible shopping is deferred until later in the week when the family car is likely to be available.

The possibility of re-scheduling trips is not an option for consumers who never have a car, so their patronage of buses simply mirrors the global rise in grocery shopping activity as the weekend approaches.

Significant variations in discretionary movement and in levels of modal captivity are observed. All population sub-groups undertake quite large numbers of pedestrian journeys, especially during weekday mornings. Those who sometimes have access to a car will ride on public transport, though they have the option of re-scheduling their activities to enable bulk purchasing at more convenient times. National figures reinforce these observed relationships between bus travel and car ownership. Households without a car record 25 bus kilometres per person per week, this falls to 9 km where one car is available and 6 km when more cars are available (Maultby 1983). Over the years 1965 to 1978/79 a 7% drop in local bus journeys has occurred among households without a car and 8% among households who have a car.

3.1.2 Mode and Area of Origin

Access to private transport is itself a reflection of local social conditions and material wealth, these factors are discussed in the present section.

The association between car travel, car ownership, and family status is apparent when study areas are ranked by their levels of access. This is done in figure 3.4 where percent deviations from mean measures of access are plotted.

Look at the percent who hold a driving licence. The areas of Heath and Rhiwbina deviate most from the Cardiff mean - their deviations amount to 36%. These are wealthier, private residential areas where licence holding is expected to be high. Cathays, close to the city centre and with much old rented accommodation, is nearest the Cardiff mean. By contrast there is a noticeable deficiency of licence holders in Llanrumney and Rumney; both are areas of low income, public sector housing. Distance from the city centre is not crucial: Rhiwbina and Llanrumney are situated at similar distances from the centre but their levels of affluence are very different.

Similar messages are conveyed by the remaining graphs, though now the poor inner city area of Roath appears to be worst. On average 30% of households are without a car, yet Roath is 29% below what is already a low average. The public housing estates continue to be associated with poor access and suffer the extra penalty of being peripheral.

The way that access to private transport is translated into revealed behaviour is illustrated by figure 3.5. The map shows the relative location of study areas, for each of which the modal split is calculated. Contributions to walk, bus and car travel are

Figure 3.4

ACCESS TO PRIVATE TRANSPORT

(Areas arranged according to the degree of deviation from the overall mean)

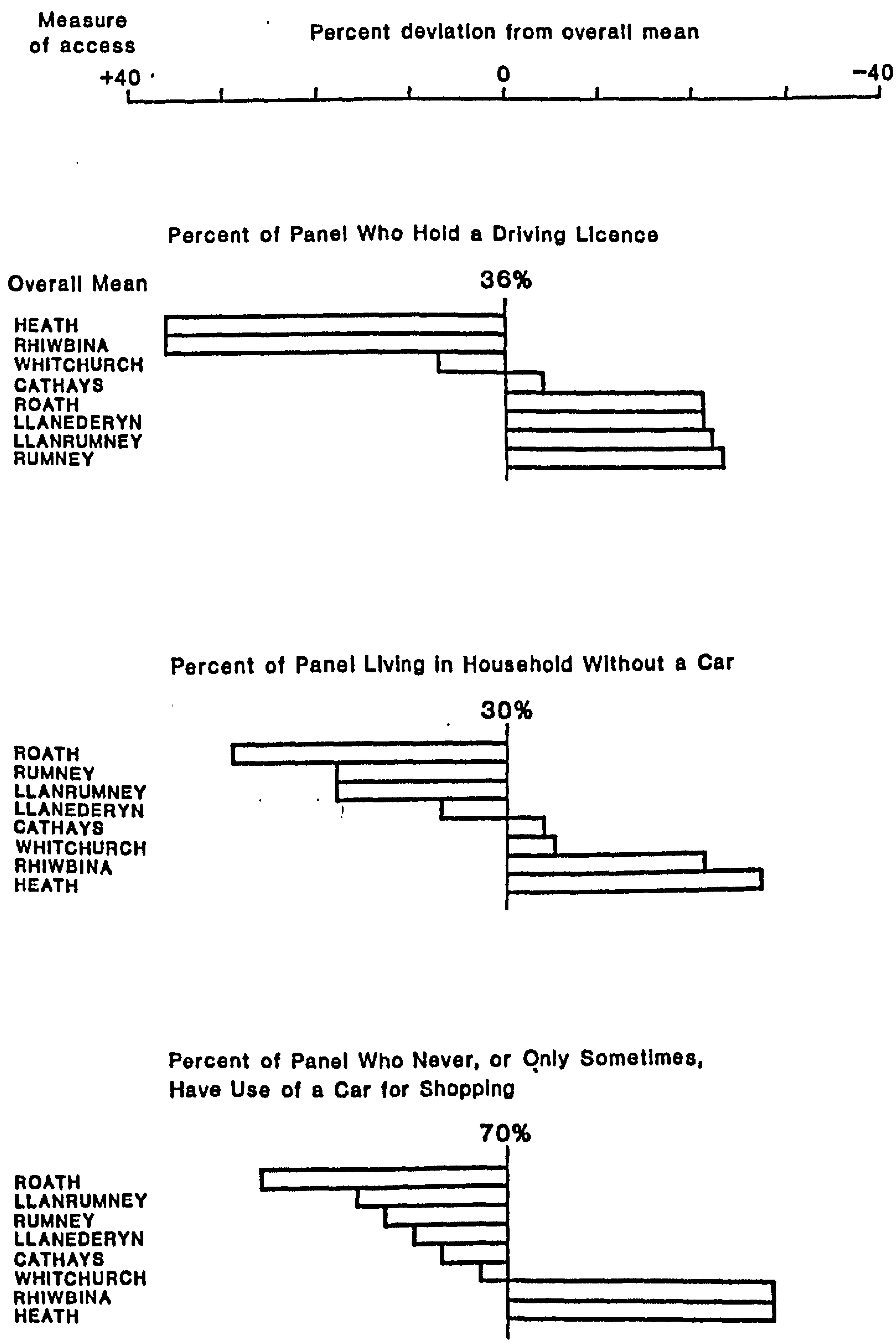
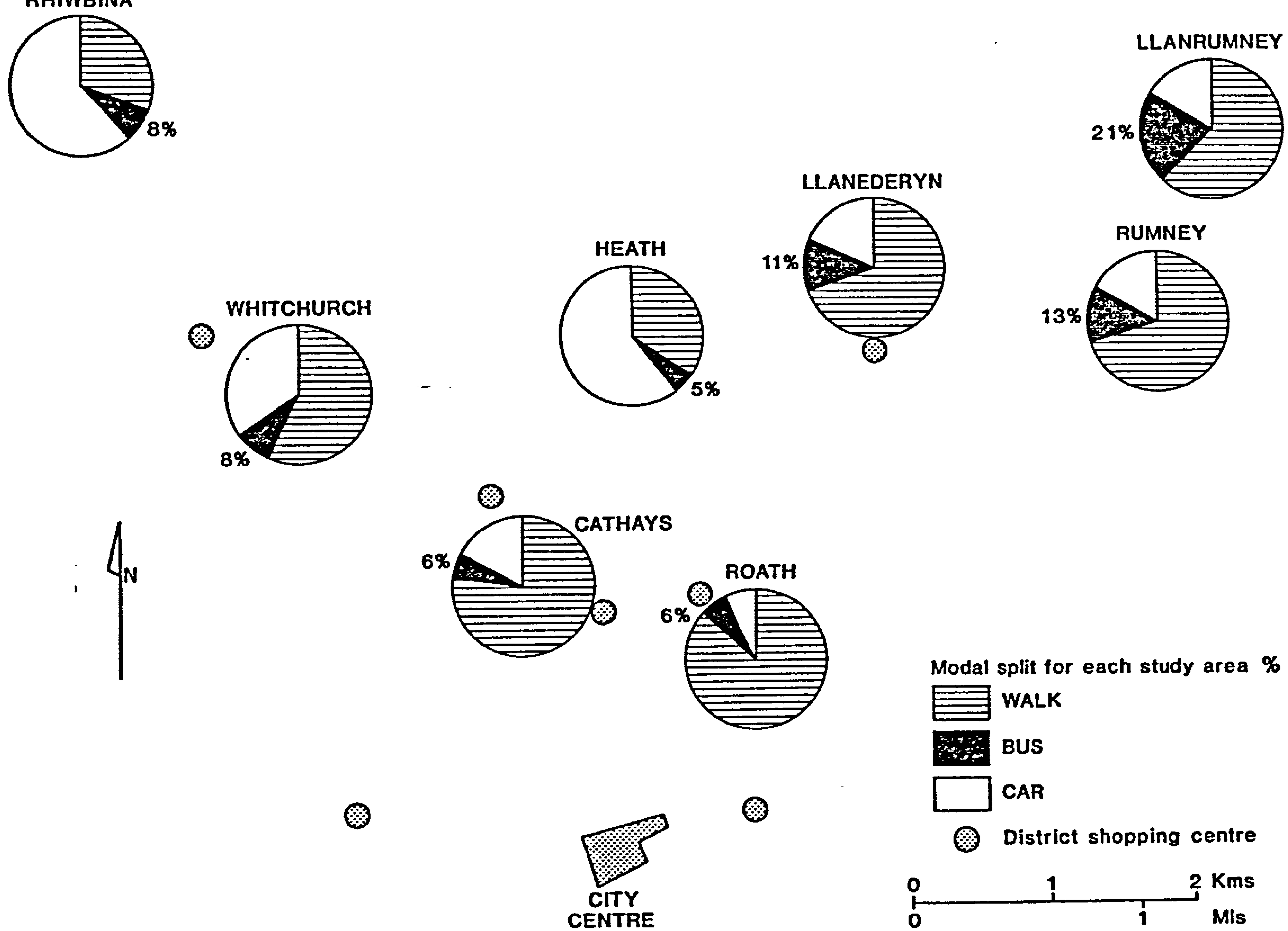


Figure 3.5

MODAL SPLIT ASSOCIATED WITH EACH STUDY AREA
(Percent based on 5-week flows from each study area)



calculated using 5-week flows from each study area (ie. only trips which originate from the home area are counted).

One conclusion stands out above all others: the dominant form of travel is walking, and this is true almost irrespective of the social status of an area. Even where the number of walks is surpassed by car journeys, pedestrian travel accounts for more than one third of all movement.

Interpretation of the fine detail shown in figure 3.5 is not straight-forward because several factors are interrelated. Modal split is affected by the socio-economic character of areas, by distance from the city centre and by the number of retail outlets in the neighbourhood. Walks are more important in areas near the city centre and close to the district centres at Albany Rd and Crwys Rd.

Car travel is dominant in two areas only; these are the more affluent suburban estates of Rhiwbina and Heath. Roughly 60% of trips are car-borne in these areas. This stands in sharp contrast to the 7% share in Roath. Even on the distant estates of north-east Cardiff car usage barely reaches 17%.

Patronage of buses is related to levels of need. Typically, inner city residents have little need for buses because they can reach most stores on foot (bus usage is 6% in Cathays and Roath). Further out, those with access to private transport prefer to travel by car. Only in areas where both access to shops and access to cars are poor do buses capture a sizable proportion of all travel. The 21% of trips in Llanrumney which are by local bus is evidence of the residents' 'access poverty' - their low mobility, their peripheral location, and their deficit of nearby shops. As a possible result the quality of life is impoverished.

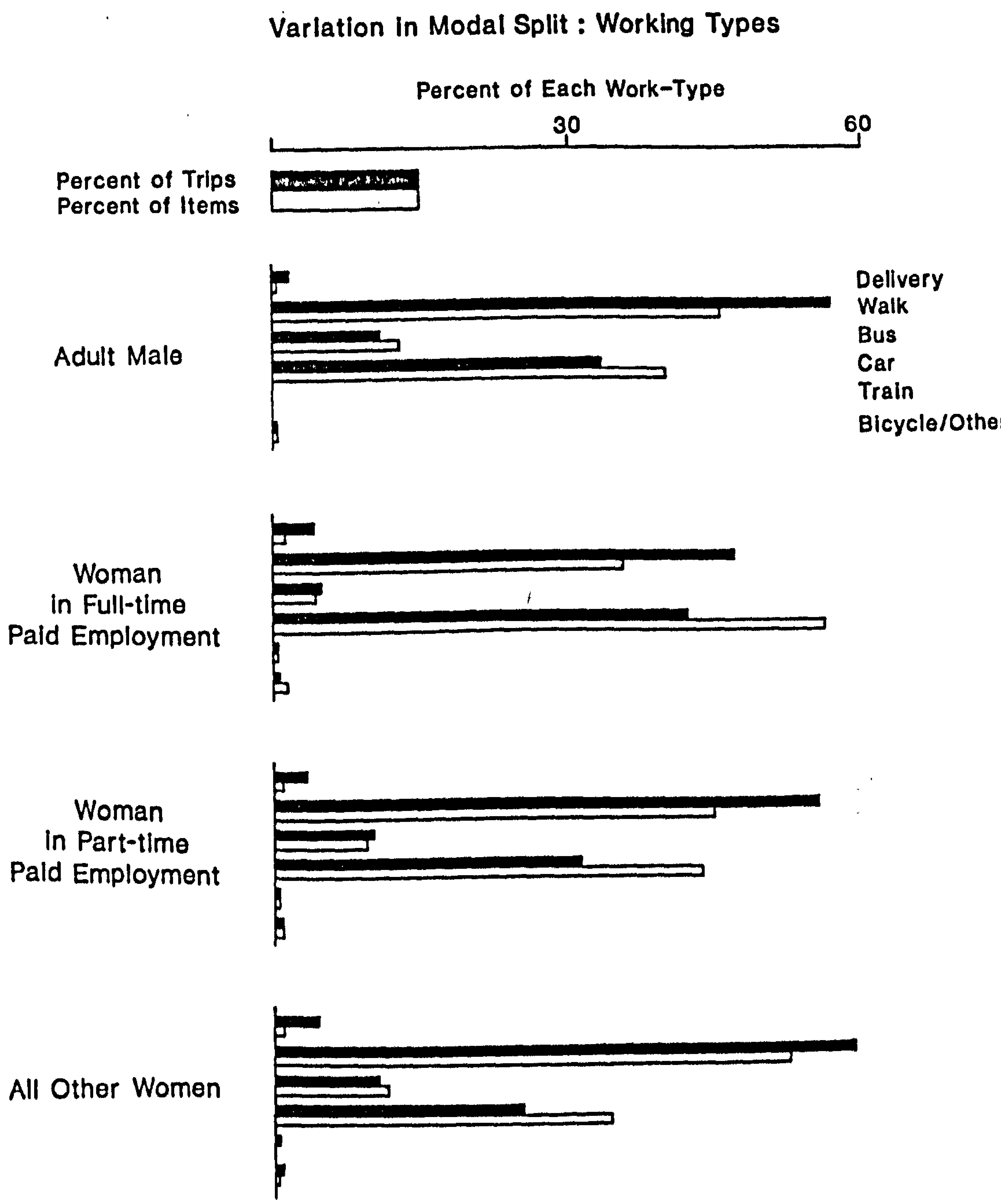
3.1.3 Mode and Work Travel

The final factor to govern modal split is journey purpose. Grocery shopping may be the sole reason for a journey, but invariably the consumer will want to visit a bank, or escort children, or call on friends. These activities will influence the form of travel that is chosen. For instance, it may be inefficient to drive to a nearby corner shop and buy bread, but not so inefficient if the shopper then crosses the city to collect children from school or goes to work.

Work travel has an important impact in two respects. Firstly, a shopper who works can combine the journey from work with grocery shopping, and in this case the choice of mode for work travel might be the dominant decision. Secondly, a shopper who works can afford to spend more on travel but has less time in which to do so. Both effects highten the degree of spatial freedom.

Variations in modal split between types of working shopper are depicted in figure 3.6. Housewives and the retired ('all other women') exhibit the greatest percentage of pedestrian trips (59%) and the least number of car trips (25%). These figures contrast with the 42% of trips by women working full-time which

Figure 3.6


Variation in Modal Split : Working Types
Percent of Each Work-Type
30
60
Percent of Trips
Percent of Items
Adult Male
Delivery
Walk
Bus
Car
Train
Bicycle/Other
Woman
in Full-time
Paid Employment
Woman
in Part-time
Paid Employment
All Other Women

are car-borne. The differences are accentuated when the percent of goods bought is studied: car travel has a 56% share among full-time working women, and 34% among all other women.

The relative importance of short-distance walks among housewives with young children and pensioners was a major theme in the research by Hillman et al. (1976). These authors showed that for people without the optional use of a car, public transport was not their main alternative form of travel. Instead, walks were more important and this was particularly true of women who did not work. Cross-cultural comparison indicates how similar situations are found in most parts of north-west Europe. Car ownership in Uppsala, for instance, reached three-quarters of households in 1971 yet among non-working women 58% of shop visits were made on foot. Even among mobile full-time workers, walks accounted for a 38% share (Hanson and Hanson 1981).

3.2 Distances, Destinations and Shopping Trips

3.2.1 Mode and Distance

Intuition alone informs us that there is a close connection between the form of travel and distance traversed. Among households with two or more cars about half the shopping trips are less than 2 miles in length, this rises to 74% when no car is available (Department of Transport 1983). As retailing has become decentralised so car usage has risen and average journey lengths have increased. These national trends provide a setting in which to study distances travelled.

Shortest-road distances have been calculated between the centroid of each residential area and shopping centres. Multiplication of these distances by the number of trips along routes actually used gives total kilometre-distances. Only trips which originate from or arrive at home areas are counted, and adjustments have been made to allow for different sample sizes in each zone. Trips which extend beyond the City of Cardiff boundary are excluded.

The key features are described in table 3.1. Modal split is expressed as a percentage of total kilometre-distance travelled. Car availability is high in Heath and only 9% of total kilometre-distance is by bus, whereas 19% is walked and a massive 73% is car-borne. No other area is quite so dominated by the car, and the mean share for the whole city is 40%.

Relative proportions are determined by proximity to facilities and nearness to the city centre. Llanrumney lies a considerable distance from the city centre and car availability is low, features which help to explain why 56% of distances travelled are by bus. The effect of low car availablity in Roath, however, is compensated by nearness to the city centre - hence pedestrian movement has a 68% share of total trip lengths.

These relationships between travel mode and distance are generalised in the next diagram (figure 3.7). Plotted are frequencies and cumulative frequencies for walk, bus and car travel.

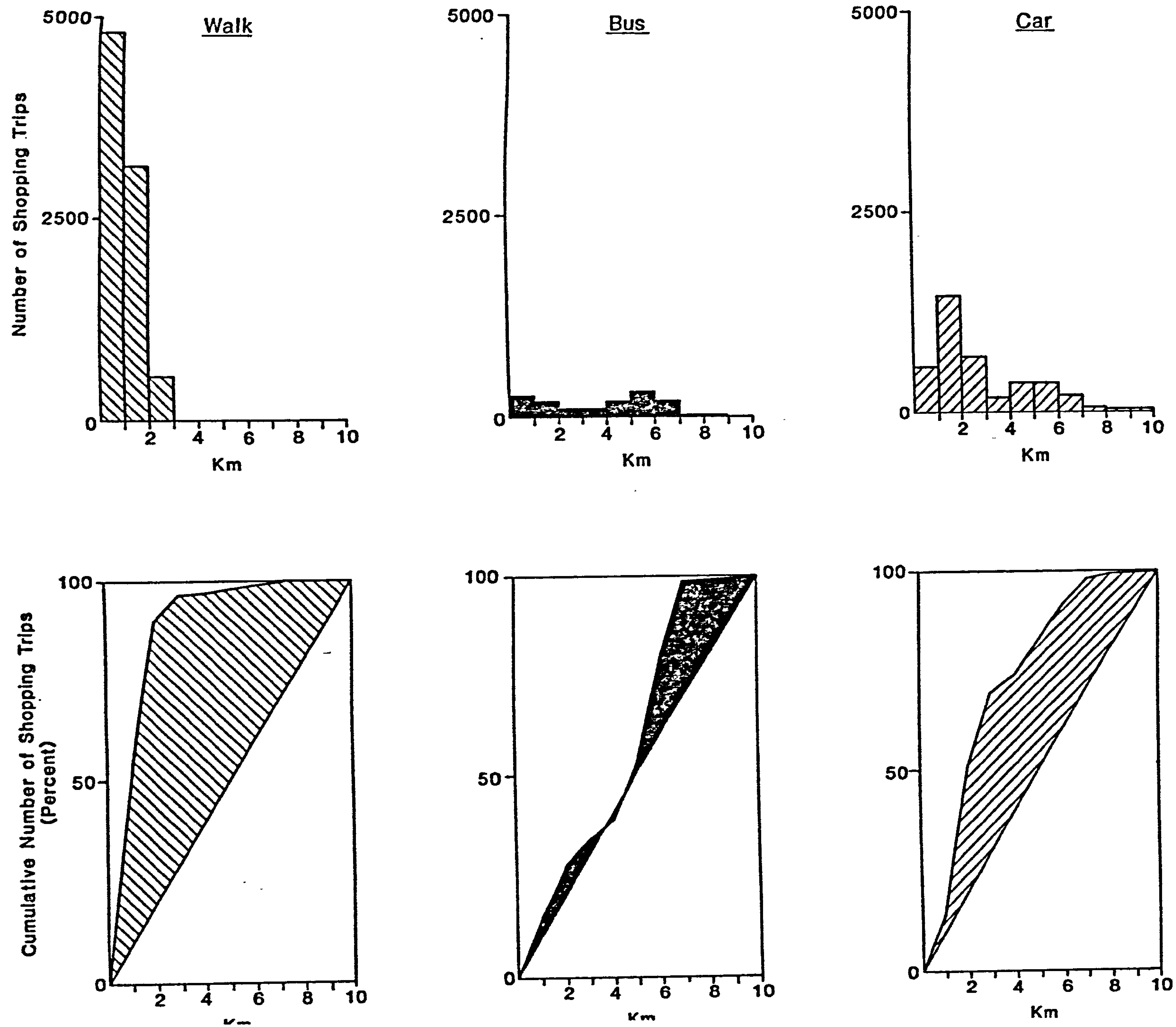
Table 3.1

Distances Travelled on Trips from Homes to Shopping Centres

Shortest-road distances, Kilometres
Areas arranged in decreasing order of car availability

Residential Area	Percent of all Distances Travelled			Total
	Bus	Walk	Car	
Heath	9	19	73	100
Rhiwbina	17	15	68	100
Whitchurch	19	40	41	100
Cathays	11	56	33	100
Llanedeyrn	21	52	27	100
Rumney	37	30	33	100
Llanrumney	56	20	24	100
Roath	15	68	17	100
Average	23	38	40	100

Figure 3.7 Distance Travelled on Trips From Homes to Shopping Centres (Shortest Road-Distance, Kilometres)



Virtually all pedestrian movement (90%) is over distances of less than 2 km. The number of trips exceeding the 2 km-band is negligible, this observation is affirmed by the cumulative frequency plot. Across all study areas the mean walking distance is 1 km, and even in Llanedeyrn (where few shops are closeby) the mean is not more than 1.9 km. There is a definite physical limit to walking, beyond which it is infeasible to carry goods.

Irrespective of distance bus usage is never very important. The distribution of patronage is bimodal, being concentrated into the ranges 1-2 km and 7-6 km. These distances are associated with travel to the nearest district centre (generally 1-2 km) and travel between suburban areas and the city centre (7-6 km where appropriate).

Car-borne trips are commonly observed in a 'spatial window' whose lower boundary is defined by the physical constraint of walking and whose upper bound is equivalent to the distance from the city centre. This 'spatial window' is most evident at distances of 1-2 km. At greater distances car travel is the only meaningful way to reach destinations, but long-distance journeys are uncommon.

Collectively these measures of distance reveal the very limited activity spaces within which people move. There are strong distance decay effects which are not ameliorated by the provision of public transport.

3.2.2 Mode and Destination

Thus far flows from each residential area have been described, now we consider the destination of these flows. Some factors which govern movement remain true whether origins or destinations are studied (spatial proximity between centres and homes for instance); in addition, observed flows into a centre will be influenced by parking facilities, traffic congestion, public transport provision and the bulkiness of goods sold.

Many of these influences are apparent in figure 3.8 which depicts the modal split associated with each district centre. Walking completely dominates movement into some of the suburban and smaller district centres; this is especially true of the Crwys Rd parade and the new Maelfa precinct on the Llanedeyrn estate. Even at the largest district centre, Albany Rd, walks represent 63% of trips. But at this level of the retail hierarchy bus and car travel become more important (despite traffic and parking problems).

For shoppers living in north Cardiff the centres at Clifton St and Cowbridge Rd East are distant and, of necessity, reliance is placed on public transport and private vehicles. About 62% of arrivals at Clifton St alight from bus journeys and the share from walks falls below 20%. At Cowbridge Rd East, lying beyond the River Taff, almost 40% of shoppers arrive by car. In interpreting these results it should be noted that the pie charts show percentages and that there are substantial absolute differences (flows into Albany Rd, for instance, are eight times those going into Clifton St).

Figure 3.8

MODAL SPLIT ASSOCIATED WITH EACH DISTRICT CENTRE
(Percentages based on 5-week flows into each district centre)

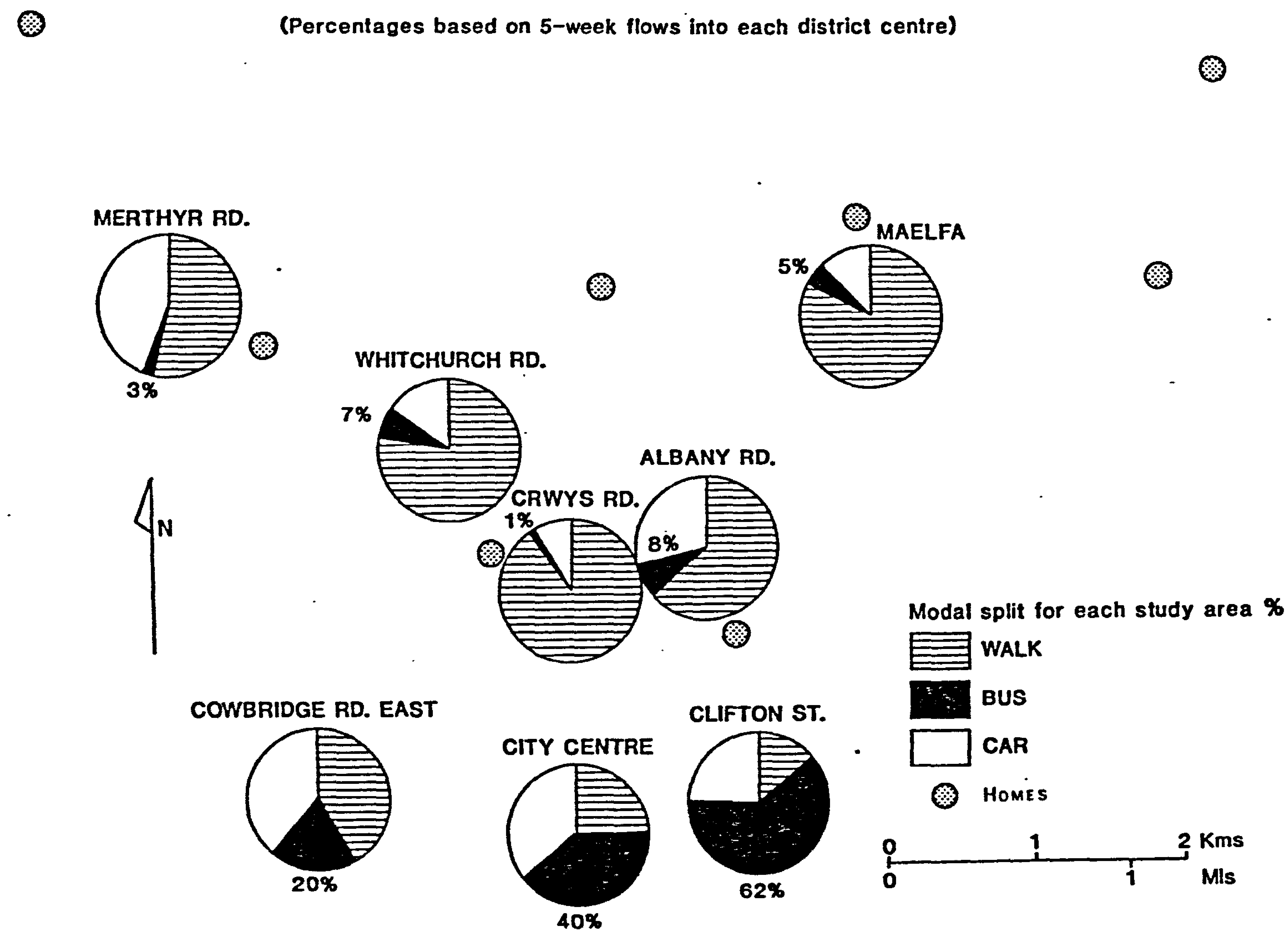
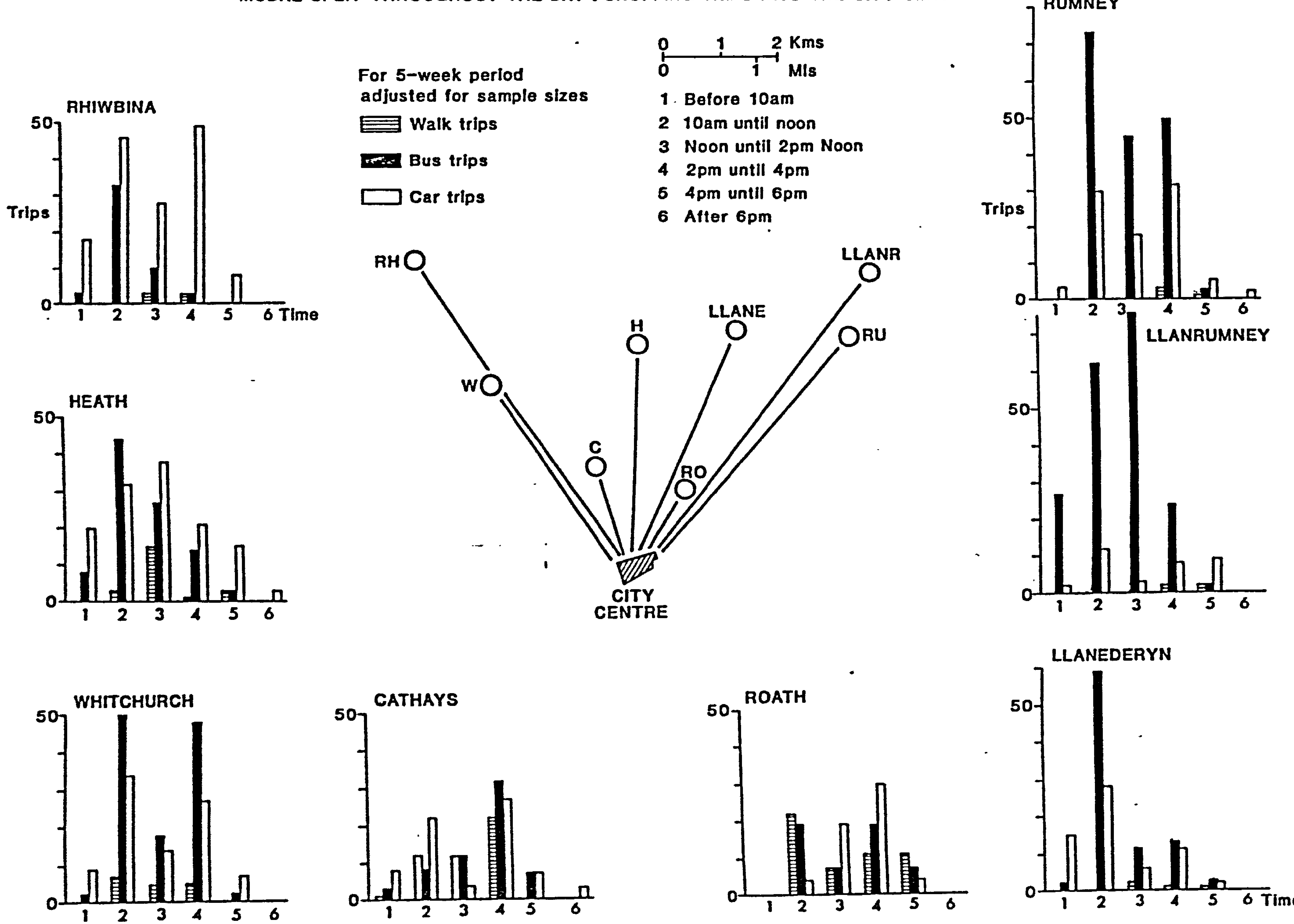


Figure 3.9

MODAL SPLIT THROUGHOUT THE DAY : SHOPPING TRIPS INTO THE CITY CENTRE



The city centre is treated separately because consumers moving into the central area reveal quite distinctive patterns of behaviour (figure 3.9). Three factors are specific to the city centre: (1) grocery shopping is easily combined with personal business and the purchase of fashion goods, (2) parking and traffic controls discourage travel by private car, (3) most of the City of Cardiff Transport bus routes converge on the central bus depot (there were some exceptions because of refurbishment at the depot during 1982).

People are far more likely to arrive by bus; indeed over 50% of consumers from Whitchurch, Rumney and Llanrumney are carried by bus. Only in Heath does car travel remain dominant (taking 71% of trips). Elsewhere proximity to the city centre gives rise to many walk trips. It is sheer proximity that explains why 30% of trips from Cathays and Roath into the centre are on foot. Differences arise because of the peculiar social and access conditions that characterise each area, though they also arise from variable levels of transport service.

There is a temporal dimension that needs to be considered too (figure 3.9). Cars are unlikely to be used during the early morning rush hour and at other times parking controls, restricted access, variable parking tariffs and congestion from delivery lorries raise problems. These reasons explain why car travel is highest from noon to 4 pm, rather than during busy mornings. The residents of Rhiwbina are exceptional in their record of morning car travel.

During the period noon to 2 pm walks assume importance from many inner city areas. While physical distance is more of a limitation on walks than temporal constraints it is possible that people avoid times when road traffic is heavy. Mothers with prams and young children and the elderly are particularly sensitive to overall levels of traffic congestion.

Bus travel is used to reach city centre shops during late mornings, lunchtimes and early afternoons. Peak patronage varies from 10 am - noon in Rumney to noon - 2 pm in Llanrumney, and in both cases bus travel dominates other forms of movement. On the whole buses are not caught before 10 am or after 4 pm. Governing bus movements are many factors associated with service provision, including weekday off-peak fares (from 9.15 am to 3.45 pm in Cardiff), fare concessions for the elderly and disabled (applicable all day except 7.30 am to 9.15 am), and crowds on buses (periods when school-children and commuters travel are avoided by shoppers). Time-budget and survey evidence from South Yorkshire confirms many of these findings about movement into the city centre (Goodwin et al. 1983).

3.2.3 Mode, Origins and Destinations

Brought together in this section are patterns of movement between residential origins and shopping destinations. Attention is confined to just two contrasting areas of Cardiff, both lie at comparable distances from the city centre and sample sizes are large.

Llanrumney is 6.9 km north-east of the city centre; the sample is drawn from a large council estate where only 14% of consumers have use of a car. Apart from 17 shops nearby at Countisbury Ave the nearest district centre is several kilometres away.

Almost 6.6 km from the city centre in a north-westerly direction is Rhiwbina. The area is predominantly private residential and, at 58%, car availability is high. There are few local shops and the nearest district centre is at Merthyr Rd 2.3 km away.

Movements from these two residential areas are mapped in figure 3.10 (a) (b) (c). These maps depict percentage flows between homes and shops for each major form of travel. Trips going beyond the city boundary are excluded.

Walks are extremely localised and no cross-city journeys are observed. Seven destinations are reached on foot from Llanrumney, and of these trips 74% end at the nearest local centre (Countisbury Ave). Even the residents of Rhiwbina, whose local facilities are poor, are only able to reach 12 destinations. Some 40% of walks are confined to Heol Ffynnon Wen which is located within the study area.

Bus trips from Llanrumney are either destined for the city centre (43% of trips) or the nearest local centre (35%). In Rhiwbina the influence of central city movement is striking (accounting for 76% of the total). The range of other destinations is very limited. Temporally there is a bimodal distribution in bus patronage: almost 50% of trips occur between 10 am and noon, and a further 20-30% occur in the succeeding period. Few trips happen after 4 pm.

Levels of service, schedules, routes and fares structure these patterns of movement. During the off-peak period, when concessions are available, services operate through Llanrumney at intervals of 7.5 minutes. Moreover, buses circle through the estate - this minimises the distance between homes and stops. The frequency and accessibility of services through Llanrumney stimulates bus patronage, even for short journeys to the nearest centre. Services are less frequent at Rhiwbina (the service interval is 15 minutes) and virtually all bus routes terminate at the central depot. It is unsurprising that consumer journeys are predominantly into the city centre.

Car travel allows the widest number of destinations to be reached, also it facilitates cross-city and long-distance movement. Despite this potential degree of flexibility most car trips are destined for nearby centres: 49% of car trips from Llanrumney terminate at Countisbury Ave, a distance well below 1 km.

For many shoppers who live in the suburbs the only way to reach inner city district centres and free-standing superstores is to travel by car. A noticeable number of consumers from both areas are able to reach Albany Rd and Leo's superstore at Splott when a car is available. At such centres bulk purchasing and variety shopping are possible. Where residents take advantage of late-night opening on Thursday and Friday they invariably travel by car to stores outside their immediate neighbourhood.

Figure 3.10 (a)

THE DESTINATION OF SHOPPING TRIPS : WALK TRIPS IN RHIWBINA AND LLANRUMNEY, CARDIFF

(Flows are expressed as a percentage of all walk trips, between homes and shopping centres, observed over a 5-week period)

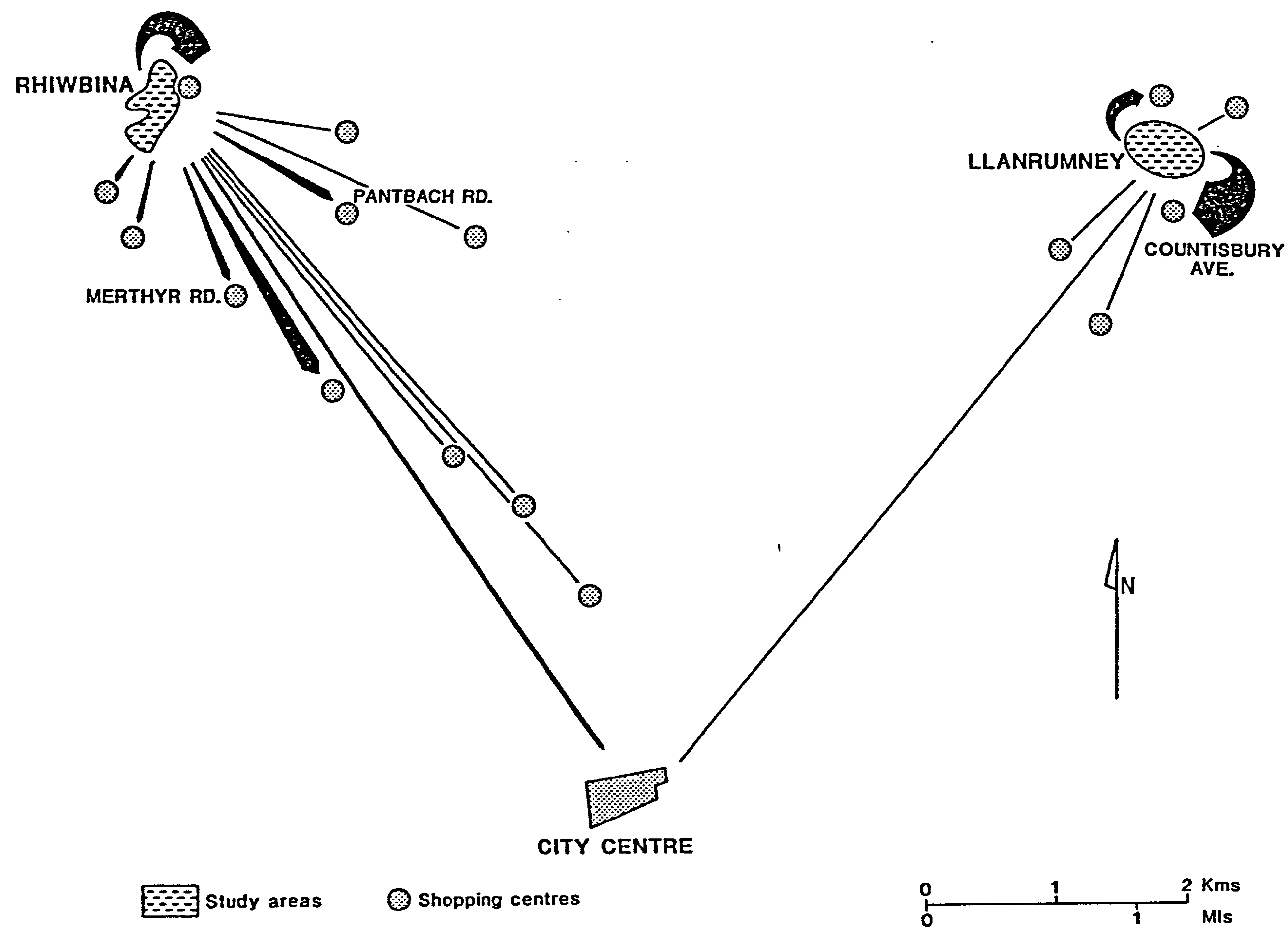


Figure 3.10 (b)

THE DESTINATION OF SHOPPING TRIPS : BUS USAGE IN RHIWBINA AND LLANRUMNEY, CARDIFF

(Flows are expressed as a percentage of all bus trips, between homes and shopping centres, observed over a 5-week period)

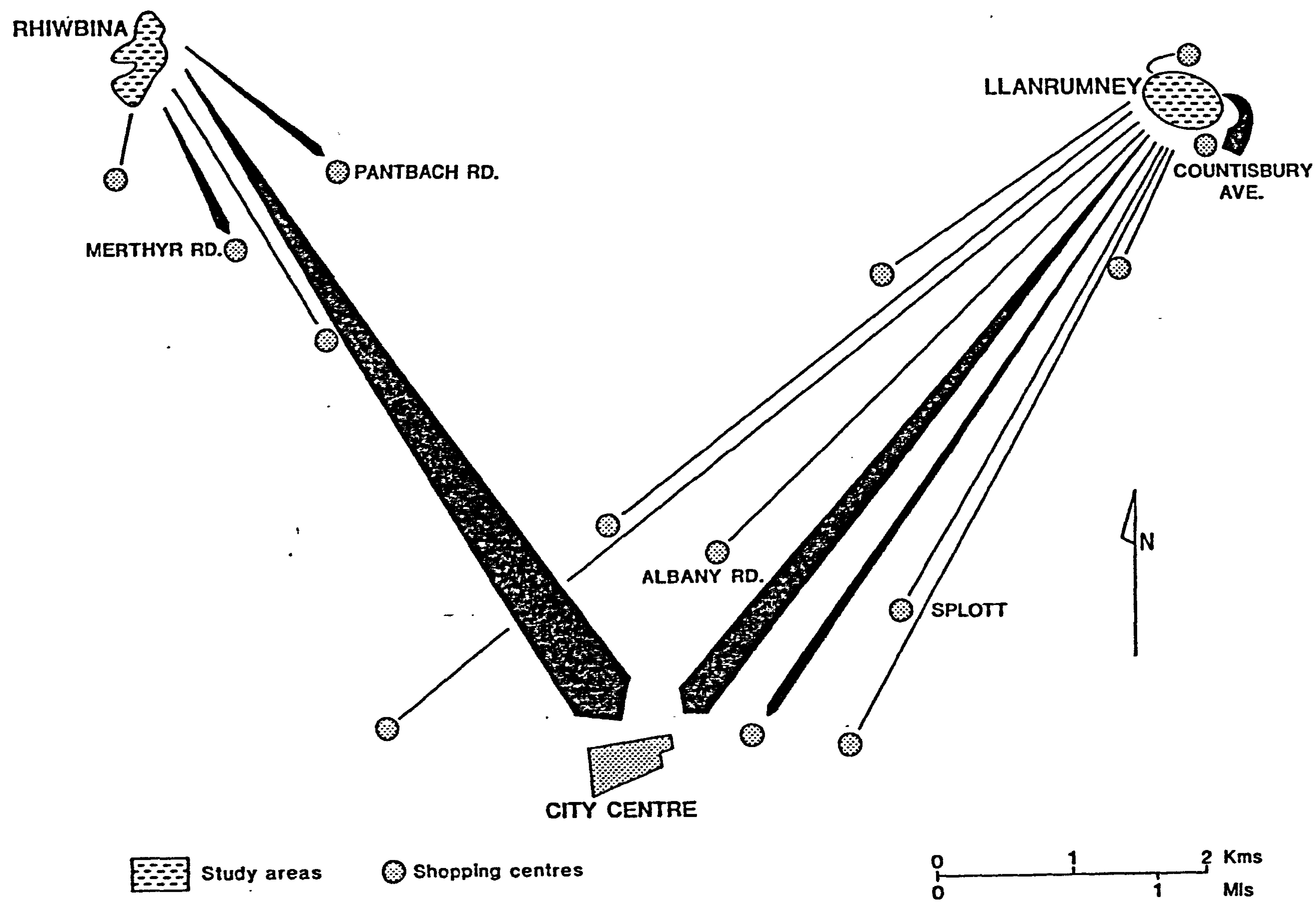
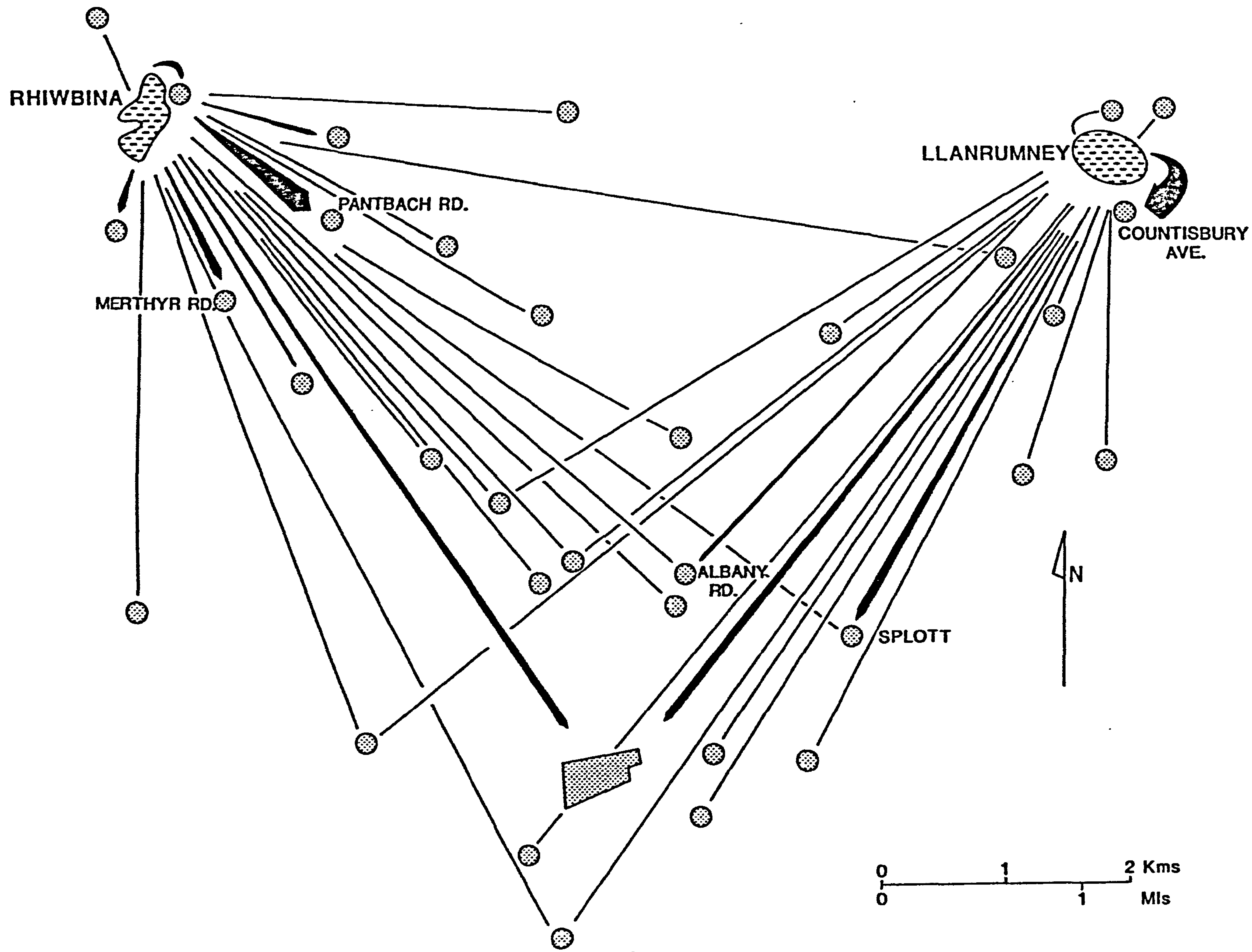


Figure 3.10 (c)

THE DESTINATION OF SHOPPING TRIPS : CAR USAGE IN RHIWBINA AND LLANRUMNEY, CARDIFF

(Flows are expressed as a percentage of all car trips, between homes and shopping centres, observed over a 5-week period)



Corroborative findings are contained in a survey of large stores; 81% of consumers interviewed at 7 superstores in Cardiff arrived by car, 14% walked and just over 3% had caught a bus (County of South Glamorgan 1984). The importance of car travel at intermediate centres and free-standing sites is unmistakable.

3.3 Discussion

Several implications stem from the empirical findings reported above.

(a) Mobility

Mode choice and patterns of movement are determined by the access that an individual has to private transport. Access itself depends upon household wealth, personal circumstances and the division of responsibility within the family.

Because access differs among people, overall measures of car ownership are unlikely to give reliable information about who travels, when and where. In practice consumers reveal varying levels of discretion and flexibility, and varying degrees of captivity to certain forms of travel.

Typically three mobility types are identified. (1) Some people always have access to a car and will tend to shop in the afternoon and evening. (2) For many, travel by car is sometimes possible if activities can be re-scheduled. At other times public transport has to be caught. (3) Those who never have access to a car rely on buses or, more likely, walk. In fact large numbers of pedestrian journeys occur almost regardless of personal mobility, and this is especially true of travel undertaken during the morning.

(b) Destination choice

Most shoppers move within very restricted activity spaces. There are strong distance decay effects away from the home, workplace and familiar routeways. These effects arise from mobility constraints, the imposition of physical limits (when carrying groceries), and from organisational constraints (such as bus timetables and the radial pattern of bus routes). Apart from rigid operational effects, there are also cognitive and perceptual filters which mould routine behaviour. Places that are familiar, or nearby, or easily referenced by landmarks are more likely to be within the activity spaces of shoppers - and repeatedly so (Marble and Bowlby 1968, Hudson 1974).

When activity spaces are divided in this manner there is scope for the emergence of local monopoly pricing and local market segmentation. When these effects are brought together it is not surprising that the behaviour of consumers appears to be repetitive and predictable.

4 Extensions

While policy relevance is not a major topic in this thesis, the foregoing empirical descriptions raise several practical issues. Some speculative thoughts are presented below, together with two examples of the links that exist between activity analysis and policy studies.

The temporal rhythms of retail activity depend upon store trading hours and upon the amount of time available to shoppers. Both aspects have been brought into policy debates in recent years. Repeated calls have been made for the repeal of restrictive Sunday trading laws and the removal of late-night opening regulations (Blomley 1985). Without legal regulation, under the provisions of the Shops Act 1950, many shoppers might re-schedule their trips to times when the family car is available.

On the demand side, the impact of recent changes is less clear. Flexible working hours and improvements to the technology of domestic life (freezers, refrigerators and household appliances) give greater freedom and reduce the drudgery of shopping. Yet women increasingly have a 'dual rule' as workers and shoppers, with the result that discretionary time is reduced (Bowlby 1984a, 1984b). Advertisers have recognised these changing patterns of life-style for several years and have used such knowledge to promote convenience foods. Today changes in life-style are beginning to affect the timing of trips, the choice of travel mode, and the destination of journeys.

Spatial aspects have policy dimensions too. Access to shops and traffic flows raise planning issues especially with regard to on-street parking, pedestrianisation schemes, provision of car parks and traffic management. Often there is a yawning disparity between revealed behaviour and the level of access that consumers desire (Bowlby 1979, Welsh Consumer Council 1982). In particular, special policies might be required for those who find it difficult to reach grocery shops - for the elderly and disabled and for mothers with young children. Activity studies show that in all these circumstances 'access' must be defined broadly to cover not only physical distance, but also time-to-get-there, cost-to-shop-there, and frequency-of-going-there.

To illustrate the links between activity analysis and policy studies we consider two areas where several commentators believe significant changes are about to occur. If expectations are met, patterns of access, retailing and distribution are about to alter dramatically. The first example is shopping from home. Technological innovation makes shopping from home feasible and among working shoppers there might be a potential market. However, there is no basis for this type of activity in current behaviour. Deregulation of local buses provides a second example. At present bus services are tied to the needs of commuters and liberalisation might simply supplement commuter services. But liberalisation might also encourage the provision of shopper and neighbourhood buses, thereby meeting a latent demand for public transport among immobile groups of people.

4.1 Shopping From Home

Retailing in Britain is undergoing significant change. These changes are liable to affect patterns of movement and distribution, and alter established forms of behaviour. New technologies are being applied to a diverse range of retail practices, including forward links to connect widely spread consumers with retailers. At present the forward point of contact is best developed in the field of videotex technology (ie. broadcast teletext and viewdata).

Several experiments have been attempted where Prestel is used for teleshopping. 'Homelink' allows customers of the Nottingham Building Society to query their accounts, make payments and participate in discount shopping using Prestel. Other schemes are operated by the Club 403 consortium and by a team from Tesco-Newcastle University-Borough of Gateshead. Both these schemes enable customers to order food from lists of branded goods which are displayed on television screens.

In Cardiff the Welsh Consumer Council (1982, 1983) has looked favourably on these experiments. It is felt that through a combination of teleshopping and home deliveries, neglected and disadvantaged consumers could gain access to the lower prices and the wider product choice available at superstores and discount stores. However, in a review of the prospects for home shopping Uncles and Ducatel (1984) show that there is little experience of this form of trading and that teleshopping may not be the panacea that some people hope.

Evidence from the Cardiff consumer panel indicates that home shopping is a relatively unimportant part of total activity. Although there was a total of 1,780 deliveries of grocery goods to customers recorded over the 24-week survey period, the average panellist spent less than 39 pence per week on home deliveries, and purchased an average of only 7 items in this way over the whole 24 week period.

When compared with other ways of purchasing goods, in-home buying is equivalent to 14% of all car-based trips and 7% of all walking trips. Among weekdays, Fridays are associated with the highest share of in-home shopping events; these being equivalent to 15% of car-based trips and 10% of walks. Clearly, when compared with travel-based shopping, purchases from the home are of marginal importance.

Diurnal patterns show that the small amount of home shopping which occurs is concentrated into a few time slots. Some 39% of calls by suppliers take place before 10 am when dairy products (other than milk) are delivered by milkmen to the doorstep. Other important times are mid-day Wednesday, most of Friday and between 2 pm and 4 pm on Saturday. These patterns reflect the influence of cultural habits and convenient delivery times. For instance, 23% of all home deliveries take place on Fridays when, traditionally, fresh fish consumption is heaviest.

In summary, revealed behaviour by consumers in Cardiff shows that shopping from home is not a major part of the existing retail scene and that emerging innovations may not reach the levels of market penetration originally envisaged.

There are several reasons why the full potential of teleshopping may not be realised. First, the current product range associated with home shopping does not provide a solid foundation of consumer demand and habit upon which retailers can build. Second, prices may remain high because of initial equipment costs, delivery costs and small-quantity orders. Other developments in retail practice may reduce demand for off-peak in-home shopping, especially relaxation of shop opening hours, flexible working hours, and the provision of shops near places of work. Finally the priorities of retailers may lie elsewhere: investment in teleshopping is considerably below that directed into backward links with distributors, and within-store electronic monitoring and stock control.

4.2 Deregulation of Buses

Major organisational changes are occurring in the bus industry and these will affect the provision of services for shoppers. In July 1984 the Government took an important initiative by publishing a White Paper (Department of Transport 1984). This document outlined proposals to remove quantity regulation and to tighten quality control. There are four areas where action is felt to be urgent: road service licensing, the structure of the industry, safety and new initiatives.

The motivation behind these organisational changes and the political debate that has ensued after publication of the White Paper has been considered elsewhere (Uncles 1984d). The response from Cardiff, however, is particularly relevant to our discussion of the activity spaces within which consumers move.

Cardiff City is one of 49 district councils which still runs its own local bus services, and like most operators it has raised fares and suffered a loss of custom. In an attempt to become more efficient, scheduled kilometres and vehicle fleet sizes have been reduced steadily. From 1977/78 to 1981/82, for instance, 3 million passenger journeys were lost. Losses in Cardiff, however, have not been as severe as those experienced in adjoining regions (Monopolies and Mergers Commission 1982).

Evidence from the Cardiff consumer panel shows that for shopping trips the main alternative to car travel is walking, not public transport. Yet many residential areas lack good quality and varied local shops. It seems likely that the latent demand for public transport is sizable and that services are inadequate. Services are inadequate in one major respect: most bus flows are between the city centre and suburban estates, whereas latent demand is for cross-city and middle-distance movements into district centres and superstores (compare (b) and (c) of figure 3.10).

Service deficiency affects many consumers, but its impact is most acute among certain segments of the population. If the bus service is poor the worst affected are the elderly and infirm, parents with young children, and those without access to a car. Survey material collected from these types of people living in

Cardiff points to concern about service frequency, inconvenient times, routes and stops, unreliability and difficulties in reaching bus stops (Monopolies and Mergers Commission 1982, Welsh Consumer Council 1982, 1984).

Neighbourhood services which run at frequent intervals through residential areas seem to be required - both panel data and survey data highlight this need. Liberalisation of local bus operations may or may not help to provide these services. Evidence from Cardiff is ambiguous.

On the one hand, the city has suffered from free competition in the past, notably when a competitor was given license to operate between the city centre and the suburban estates of Cyncoed and Llanrumney. C K Coaches (Cardiff) Ltd functioned during 1981 and part of 1982, and there was considerable rivalry over service frequencies and fares. This experience proved to be costly for both operators and confused many consumers. In March 1982 the private company went into receivership with debts of £70,000. The important point to note is that the private operator duplicated existing centre-suburban routes, and its aim was to capture the commuter market.

On the other hand, many of the recommendations put forward as 'new initiatives' in the White Paper would begin to satisfy the latent needs of shoppers. For instance, reference is made to sponsored buses and free buses operated by retailers. It so happens that these ideas have been implemented already in Cardiff. In 1983 Tesco started to run a free bus; this passes through the northern suburbs of Cardiff to reach the new hypermarket east of Llanrumney. Orderly deregulation seems to be required if the right balance is to be found between service duplication and service innovation.

These brief comments have drawn attention to the policy issues that are associated with activity analysis, they are not intended to be comprehensive and it is for future researchers to explore their full significance.

PART II

MODELLING and DESCRIPTION

Formal models of consumer behaviour are used to extend the descriptive studies of Part I. Emphasised is the need to condense information, to look for salient messages, to identify crucial variables and to provide an holistic view of temporal and spatial processes. For these reasons greatest attention is given to the applied aspects of modelling.

All applications relate to shopping activity, and some specific themes include the study of trip frequencies, the linking of shop visits with other activities, and the choice of transport to reach shops.

The next three chapters are organised around two natural sequences: between chapters there is a steady rise in the amount of structure that is brought to bear on the data; within every chapter the progression is from basic principles, through substantive findings, to model assessment and extensions.

Modelling starts in chapter 3 with a classification of consumer activity. The primary task is to elicit the salient features of panel data without imposing too many preconditions, assumptions or constraints. Classification provides an uninhibited 'first look'. A feel for the data is acquired and topics worthy of further investigation are isolated. At this stage no distinction is drawn between behavioural responses and observed variables.

The adaptation of cross-sectional and regression-type models is considered in chapter 4. The two basic elements of panel data are incidence and choice, and these are examined using simple probability models. To specify these models, parametric assumptions are made about the distribution of random components. A definite structure is imposed on the data.

Finally, an integrated approach is set forth in chapter 5. Full advantage is taken of the longitudinal nature of the consumer panel. The integrated model handles repeated states; these refer to the choice of travel mode, the timing of a purchase and the number of occasions when a particular bundle of shopping activities is observed. Further parametric assumptions are made concerning the distribution of unobserved components and temporal processes.

A second sequence underlies each chapter. Methods are introduced step-by-step and simple geographic examples are used to illustrate the basic principles. The Cardiff consumer panel provides all the material for substantive studies, and results are summarised through a series of examples. These examples refer to travel and scheduling decisions, such as the choice of travel mode and the decision to combine shop visits with other family maintenance activities. Studied too is the influence of variables that are of interest to market researchers, planners, and retail managers, and which give insight into the behaviour of consumers.

The next step is to assess the findings. Many issues could be examined: sensitivity and robustness, specifications and transformations, model comparison, spatial and temporal dependence. Here the approach is selective; the focus is upon some of the more innovative tests and those most suited to panel data. This involves the analysis of stability and sensitivity. The integrated approach of chapter 6 also enables temporal effects to be appraised, including the effects of omitted variables and heterogeneity, feedback and temporal dependence.

Tests of a model serve a dual purpose. Essentially they should validate the substantive findings and help us to refine the model. A more fundamental purpose is to lay down a challenge for future research: statistical 'problems' beget geographical 'resources'. In recognition of these challenges each chapter concludes with comments that are tentative and speculative. A wider literature is drawn into the discussion and it is evident that there are many opportunities for grafting together ideas from different disciplines.

CHAPTER 3

CLASSIFICATION AND CONSUMER ACTIVITY

The handful of sand looks uniform at first, but the longer we look at it the more diverse we find it to be. Each grain of sand is different. No two are alike.

Robert M. Pirsig (1974)
'Zen and the Art of Motorcycle Maintenance:
An Inquiry into Values'

1 Introduction

1.1 Classification

At the outset two issues need to be clarified: (a) the purpose of classification, and (b) the best manner by which data are to be classified. Methods to classify data are numerous and selection is best achieved from experience. A definitive statement on this matter awaits the presentation of examples, meanwhile some general remarks are made.

1.1.1 The Purpose of Classification

Classification is a way to organise and simplify data. A kind of 'multivariate histogram' - in which each bar of the histogram is relatively homogeneous - is how Hartigan (1975) has aptly described this technique. Many other objectives are ascribed to classification, such as the inference of latent features of human behaviour and the prediction of future behaviours. These wider issues are not examined here: our aim, quite simply, is to organise and simplify data.

The need for classification rests in a dilemma: the capacity to expand the data matrix has not been matched by the capacity to understand its contents. Automated stock control, monitors at the point of sale, and laser scanners at the checkout all represent more accurate forms of retail measurement, and open up possibilities for better management and planning. Computer-based systems provide the means by which these data can be stored and accessed. Yet, simultaneously, the need to reduce the size and complexity of the data matrix becomes more urgent. To be meaningful, the data must be reduced so that the central themes stand out.

The dilemma is not new. Rapid expansion of the data matrix was one justification for the modelling effort in geography (Haggett and Chorley 1967). Likewise, Ehrenberg and Twyman (1967) noted how routine audience measurements from JICTAR were generating 500 million separate measurements per annum, most of which lay unexamined and unintelligible - until a search was made for salient patterns and themes. Both these efforts occurred when computer-based gathering and storage systems were beginning to assume importance; now the problems of information handling are more acute.

Just as the dilemma is not new, so classification is not a novel response. The reasons for classification that are evident in Aristotle's work remain true; he sought order, pattern and elegance, and we do likewise. The objective is to condense information through the removal of noisy and unimportant variation and to isolate things which are really important.

1.1.2 Ways in Which to Classify

Much insight can be gained from a knowledgeable guess or from commonsense. Most classification is of the commonsense variety - brands are allocated to the set of product fields, placenames are allocated to the set of proper nouns. Conventions tell us how this is done. Yet even commonsense classifications are by no means natural and universal; we allocate brands to product fields using information about their contents, other people might discriminate on the basis of colour, or viscosity, or taste. Current advances in artificial intelligence and in programming languages take advantage of these conventions in commonsense classifications.

When faced with large quantities of data the possibility of using expert judgement, or mental rules, or commonsense, is less feasible. The allocation of ten brands to two product fields from data about their contents is trivial; when there are ten times ten brands and numerous attributes (contents, colour, taste, etc) a non-manual method is needed. Automated numerical methods give precise solutions based upon clear logical rules. Logical rules allow some function to be optimised; it might be partitions that are optimised, or the coherence of groups, or the hierarchy of groups. Precision and clear rules do not mean that the whole process is objective: some decisions are formalised within the program, others - such as the choice of attributes, the choice of algorithm, and so on - are left to the researcher.

Undoubtedly numerical methods have dangers. Classification techniques, some argue, provide effective numerical solutions to the wrong set of questions. Final groups are too readily seen as stereo-types, in the negative sense of labelling and constraining subjects. Moreover, researchers have sometimes been motivated by the 'computernik' factor rather than by sincere interest in the subjects of a classification. These remarks, expressed by Johnston (1968), Cormack (1971) and Jardine and Sibson (1971), are warnings. Dangers are heightened in human sciences because of the tendency to infer latent meanings; these meanings belong to metaphysics not to data description.

Application across numerous disciplines has led to the emergence of many slightly different methods, which makes the selection of an appropriate method extremely difficult. Numerical methods are strongly represented in biological taxonomy, plant ecology and soil science. Resort to numerical methods is common in biomedical and psychological research, and is often performed using the CLUSTAN package (Wishart 1978). The search for pattern in data relies upon similar principles and applications are found from agriculture (Williams 1976) to transport (Recker et al. 1983).

A broad review of this literature is superfluous since reference can be made to several introductory statements (Hartigan 1975, Lorr 1983, Semple and Green 1984). Marketing applications are commented upon by Frank and Green (1968) and applied to panel data by Rao and Sabavala (1981). The relationship between classification and regionalisation is fully elaborated by Haggett et al. (1977, 450-90), and Johnston (1976).

Despite terminological confusion and the profusion of review articles, there are only two main methods: division and agglomeration. These are depicted in figure 1.1.

(a) The Divisive Method

Logical division starts with all data contained in one group and splits from the top down. Splitting is achieved using the most effective attribute or a collection of attributes. At each stage the group which is least homogeneous is split.

(b) The Agglomerative Method

Data for each individual is used to group from the bottom up. Numerical grouping is achieved using a collection of attributes. At each stage the most similar individuals are fused together.

The most important decision to be made is the choice between a divisive or agglomerative method. Conventionally another important distinction has been drawn, that between hierarchical and non-hierarchical strategies. Hierarchical strategies seek to optimise the 'route' by which data are classified, these have a long pedigree in numerical taxonomy. Non-hierarchical strategies, on the other hand, are designed to optimise 'partitions': well-defined groups are obtained serially or simultaneously. A full decision plan is laid out in figure 1.2.

More recently hybrid strategies have been adopted. A divisive strategy, using one or many attributes, generates an initial allocation of individuals to groups and at this stage the hierarchy is preserved. Further iterative reallocation enables homogeneity and partitions to be improved, and the final solution is non-hierarchical. For the reasons that follow these hybrid models are selected to investigate shopping activity.

To organise and summarise data on shopping activity several criteria need to be satisfied. Collectively these criteria point to a polythetic divisive method that has the option of final iterative reallocation.

(1) Desired are homogeneous groups which are well partitioned. The final solution need not be hierarchical since the route, or dendogram, is unlikely to have any substantive meaning. While homogeneity is a reasonable aim (it implies that within-group variance is less than between-group variance) other objectives might be required under special conditions (equal numbers in each group might be desired or a contiguity constraint might have to be met).

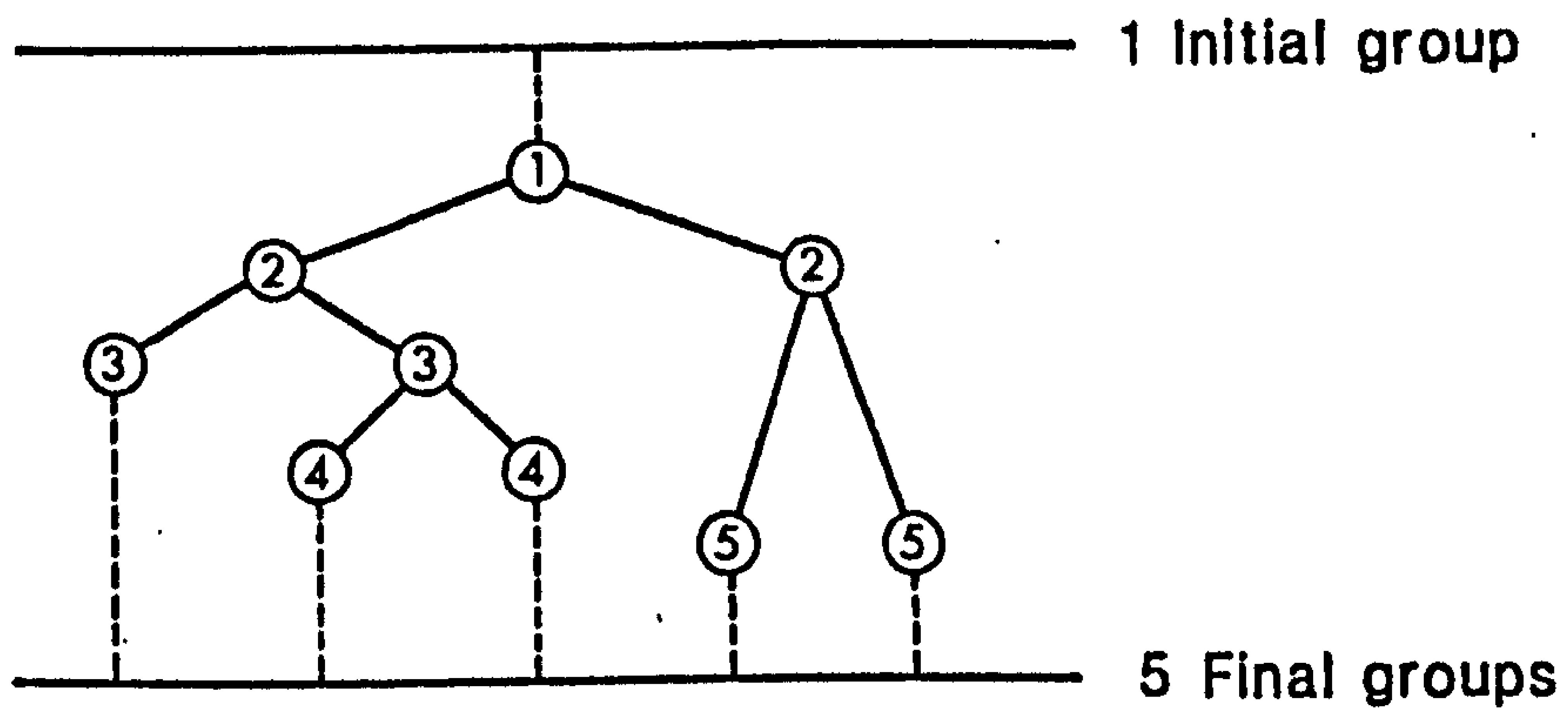
(2) Groups should be defined from a wide number of relevant attributes, ie. a polythetic solution is sought. Aspects of activity are measured on many scales, so attributes are not only polythetic they are also mixed. Traditionally association analysis was applied to mixed data, this proved unduly sensitive to outliers and has been replaced by iterative polythetic division. Surprisingly little attention has been given to mixed data classification and there are virtually no examples in geography.

(3) The method must be efficient in order to handle hundreds

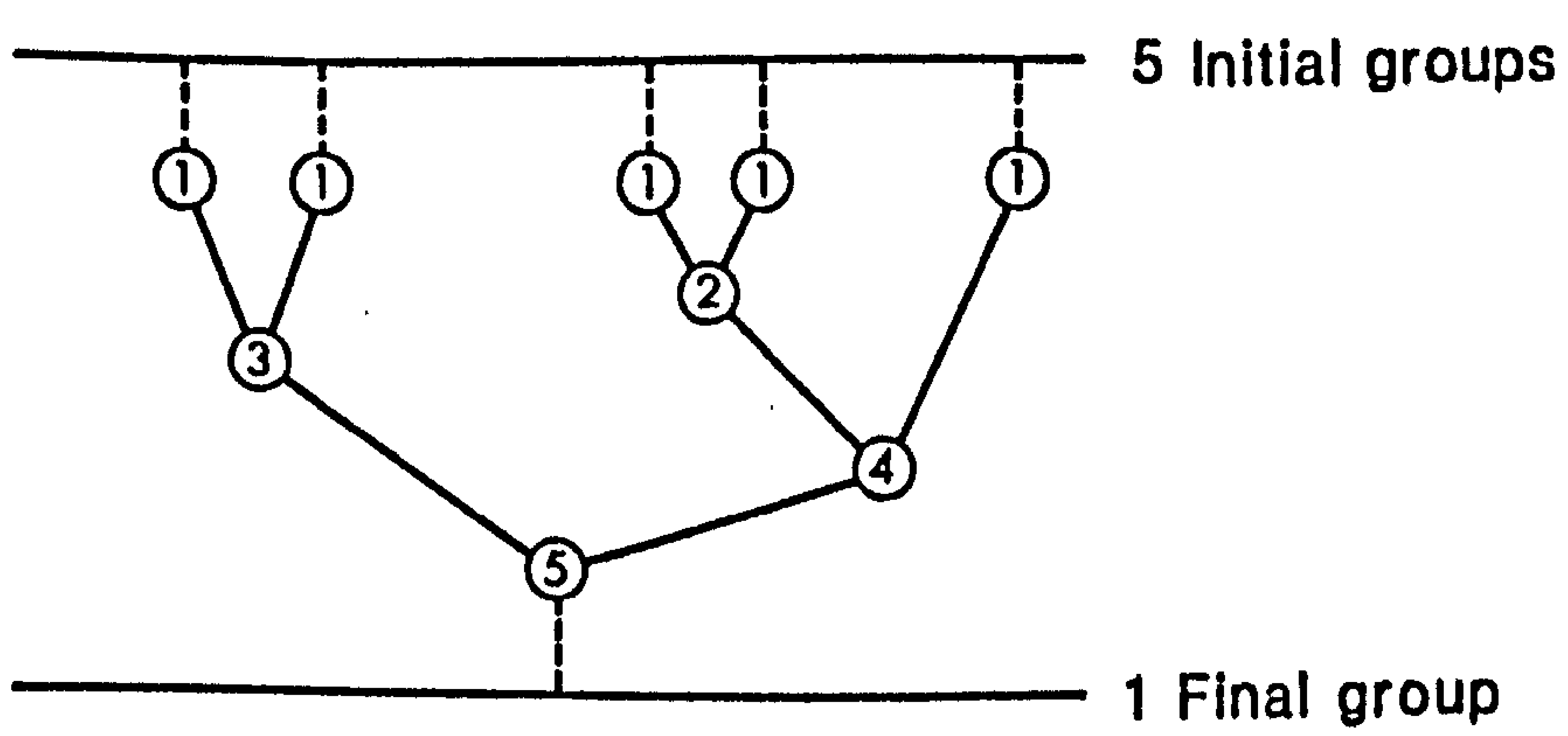
Figure 1.1

CLASSIFICATION : TWO ALTERNATIVE METHODS

(a) THE DIVISIVE METHOD



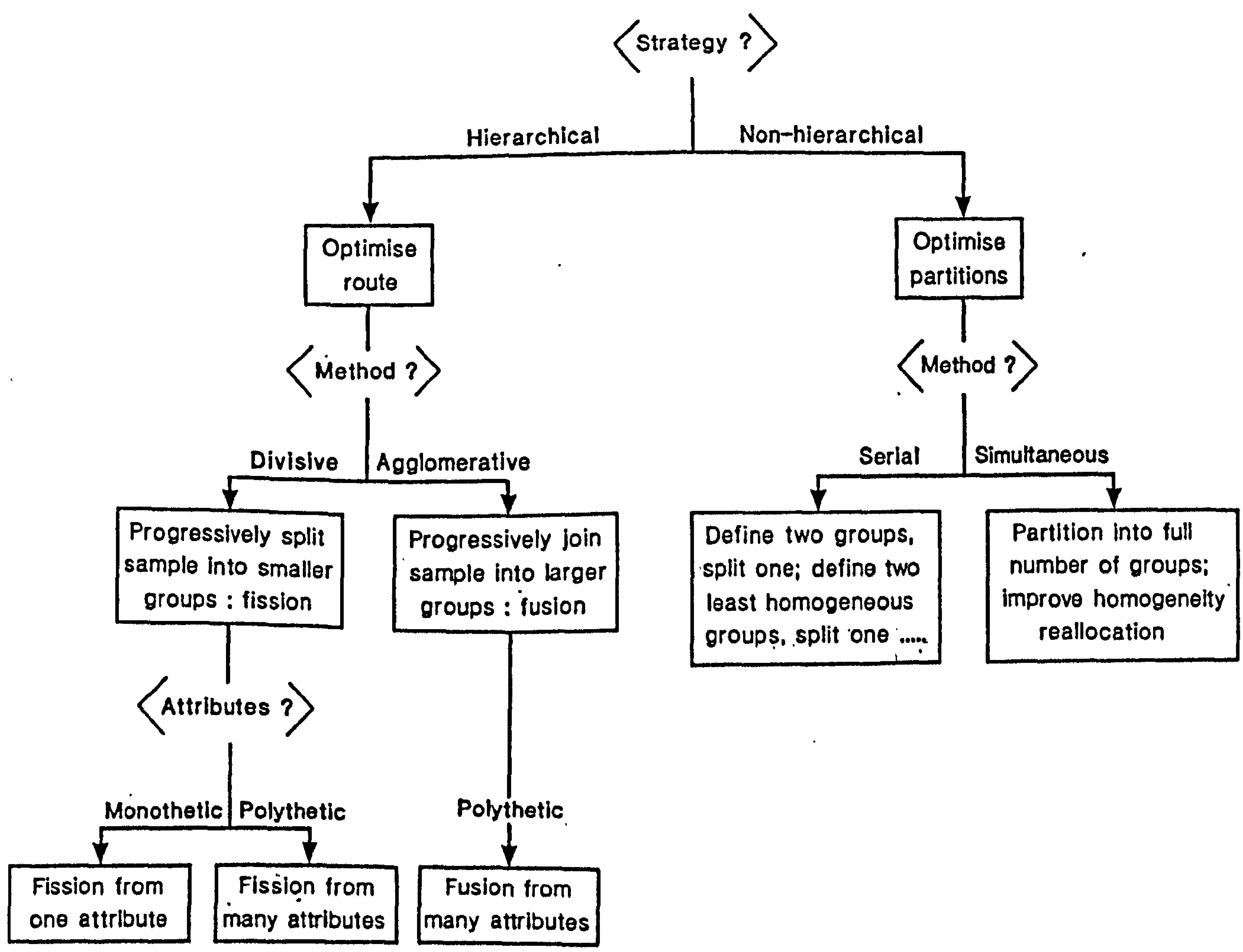
(b) THE AGGLOMERATIVE METHOD



Numbers refer to the stage at which partitions and linkages are made.

Figure 1.2

CHOICE OF CLASSIFICATION TECHNIQUE : DECISION PLAN



of records. As a rule, when the number of individuals is high and attributes are few a divisive strategy is chosen (because no inter-individual similarity matrix is required). The only sensible treatment of shopping activity data is divisive.

In subsequent sections polythetic division is explained and illustrated. A simple example is given in order to work through the basic principles by hand. Then several large examples are presented. Attention is given to how the algorithm generates an efficient allocation of individuals to groups, where each group is regarded as a 'bundle' of shopping characteristics. Adoption of classification enables complex data to be simplified and summarised.

A further step involves the appraisal of polythetic division. Appraisal is considered in two parts: assessment in one instance is internal, and in the other case it is external. Section 3 provides an internal assessment: an investigation of stability and replication shows that both the method of classification and the findings are robust. The need to consider robustness is often expressed, yet rarely is it heeded. One good exception in geography is the work of Openshaw and Gillard (1978), while Lorr (1983, 104-121) mentions some non-geographical examples.

In section 4 a different approach is taken: the efficiency and results of polythetic division are compared against an alternative iterative partitioning procedure, namely K-means clustering. While results are not wholly equivalent, the degree of consistency is encouraging. K-means clustering is a serious alternative, but only the method of polythetic division is capable of working with fully mixed data.

1.2 Polythetic Division

In this section the principles of polythetic division are sketched and some examples are worked through by hand. A number of detailed features are explained and justified. Specifically, seven issues are addressed: choice of attributes, primary division, reallocation between groups, secondary division, reallocation between all groups, assessment of each attribute and the optimum number of groups.

The version of polythetic division applied here is essentially that described by Lance and Williams (1975). Lance and Williams indicate how a number of algorithms within the TAXON library are useful for divisive classification, the main one being REMUL. Subsequently the algorithms have been improved and the flowchart in figure 1.3 attempts to summarise the structure of the most important algorithms now available (viz. DIPCAN, RECAN and CRAMER).

The sequence starts with data for N individuals and J attributes. The desired number of final groups K is specified at the outset. After the data are checked for missing entries and invalid entries, a matrix of inter-attribute correlation coefficients is found.

Figure 1.3

DIVISIVE POLYTHETIC CLASSIFICATION : ALGORITHMS

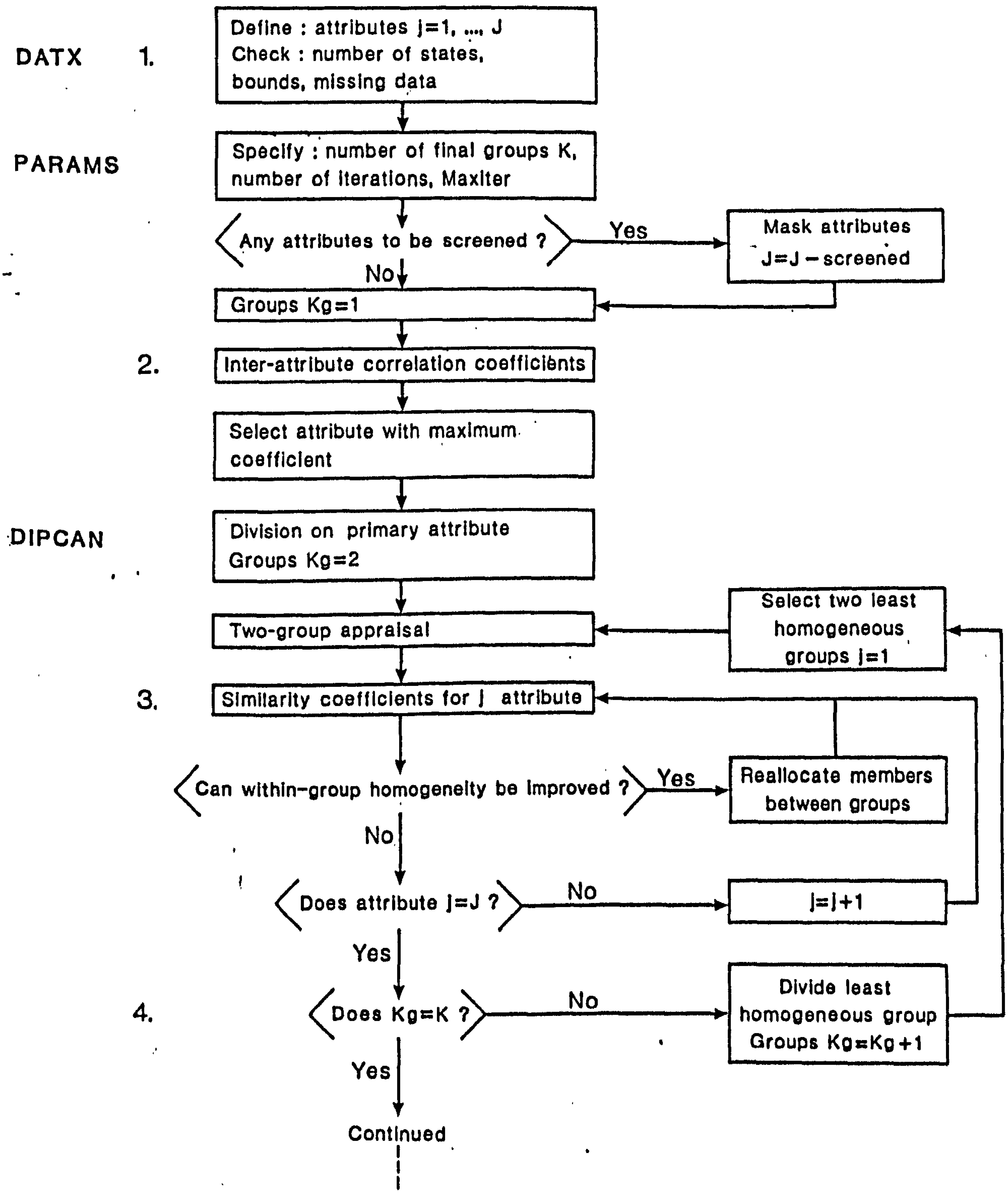
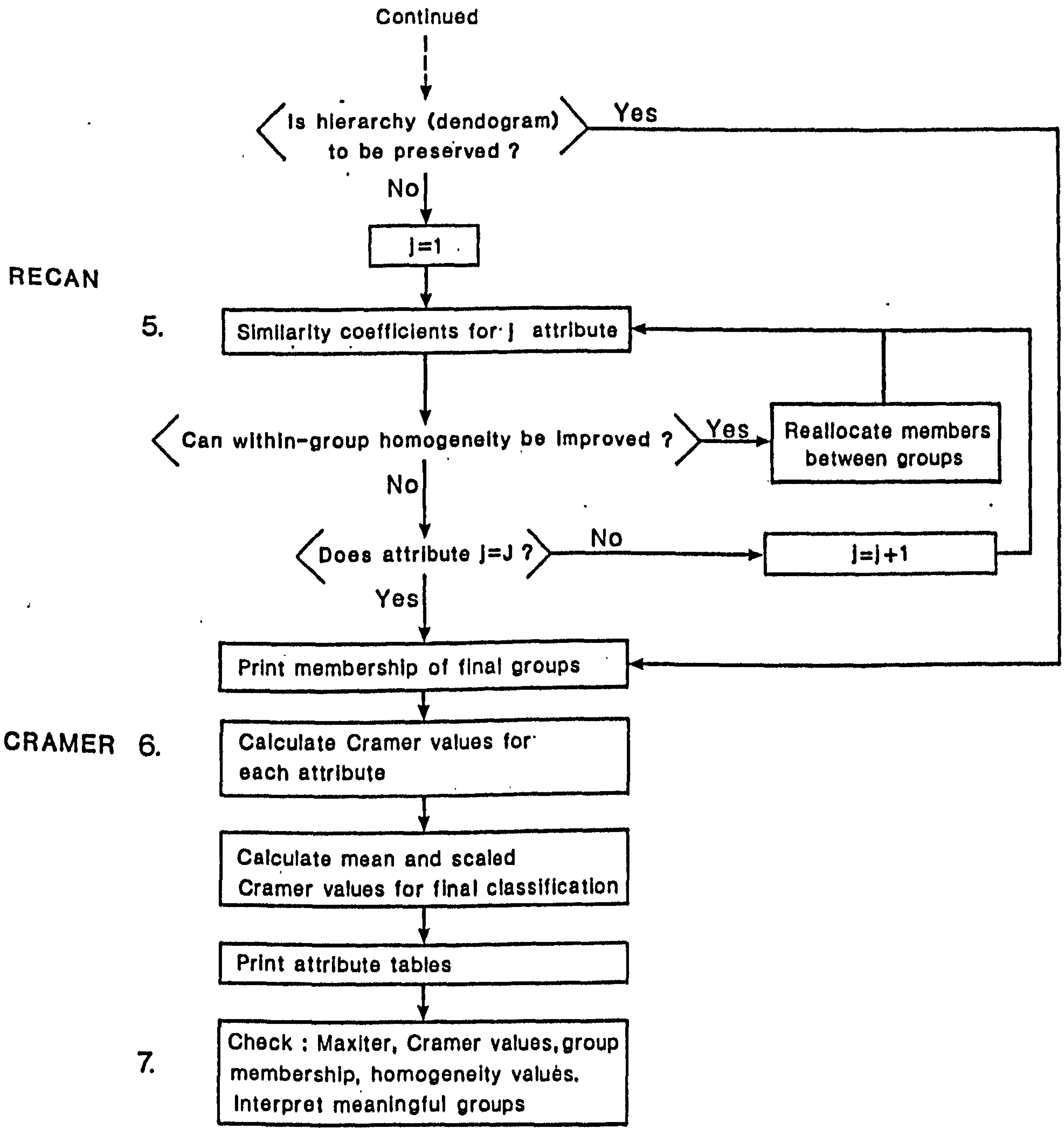


Figure 1 3 (cont.)



The names of TAXON algorithms are printed in the first left hand column.
Numbers 1 to 7 in the second left hand column are explained in the text, sections 1.2.1 to 1.2.7

From these coefficients a primary attribute is identified and used to define initial groups. An iterative partitioning procedure is set in motion which aims to maximise within-group homogeneity. Once all individuals have been allocated to K homogeneous groups further reallocation is allowed, this improves partitions but destroys the divisive hierarchy. Finally, details are reported for the composition of each group and the contribution of each attribute.

Indicated in the left hand column of figure 1.3 are points that need to be elaborated, these are discussed in detail in the following sections.

Example: The Classification of Shops

1.2.1 Choice of Attributes

Most geographic studies draw upon a variety of data types, and classification is no exception. Consequently algorithms for mixed data are needed. The number and availability of comprehensive algorithms for mixed data is limited. One of the few sources is the TAXON library. Algorithms in this library also have the virtue of being able to cope with missing data. Missing entries are undesirable yet most complex social surveys and panels are going to have a few gaps, so the ability to handle missing data is crucial.

Four types of attribute are defined:

(a) Qualitatives

These are binary attributes which denote the presence or absence of a feature. For computational purposes it is helpful to view presence or absence as two binary states.

(b) Disordered multi-states

Attributes which have a number of discrete or exclusive states are termed multi-states: car, bus and bicycle for example. These are disordered because the arrangement of states is unimportant. Within each state the feature is either present or absent; the state 'car' may be occupied - 'yes there is a car' - or not - 'no there isn't a car'. In practice, there is little computational difference between qualitatives and disordered multi-states.

(c) Ordered multi-states

Attributes have a number of discrete or exclusive states and their order is meaningful. States might range from strong preference, through preference, indifference and dislike, to strongly dislike; the difference between strong preference and dislike is much greater than the difference between strong preference and preference. Strictly these attributes are interval, but for computation they are re-expressed as nominals or numerals.

(d) Numerals

Attributes which vary continuously over a range of values are numeric. Trading turnover might range from £8,000 to £1 million for example. Often counts (meristic attributes) are described as numerals, the correctness of such an approximation will depend on the number of frequency classes.

These are the four basic types of attribute. In addition, non-exclusive or linked attributes are defined as a sub-set of disordered multi-states. Individuals may occupy several states in a non-exclusive attribute. For instance there are about 6 major brands of coffee being sold in Britain today; we want the complete set of brands to contribute the equivalent of one attribute yet still allow consumers to purchase several brands. To this end coffee brands are treated as non-exclusive disordered multi-states.

All types of attribute are reported in the analyses which follow. It is unusual to find the full range of data types in classification and pattern analysis, yet a careful examination of complex activity requires just such breadth. Certainly earlier studies of complex activity patterns have not been fully specified because of an inability to handle all data types.

An example is introduced to illustrate the different types of attribute and then to assist in working through the principles of classification. The number of shops selling grocery goods within a city the size of Cardiff is large (over 1,000 shops are recorded in the Cardiff survey). Characteristics to descibe these shops are available from field surveys: we know about floorspace, goods sold, number of checkouts, number of shop assistants, and so on. The aim is to use information about store characteristics to group shops. Final groups might be related to functional zones in the city or used as a scheme for quota sampling in a future survey.

Artificial data are shown in table 1.1. A random sample of 7 shops is described by 8 attributes. Four attributes are qualitatives, three are multi-states and one is numeric.

Four binary attributes record the presence or absence of each feature: whether car parking facilities are inconveniently placed in relation to the shop, whether sales staff are helpful, whether the shop has a delicatessen counter, and whether frozen foods are sold. Information of this sort is obtained from direct observation or from attitudinal surveys among customers.

Functional type illustrates attributes that are disordered multi-states. There are 7 functional types (states) such as superstores, supermarkets, superettes, etc. Shop 1 belongs to functional type 4, shop 2 to functional type 3 ... Brands-of-coffee, as an example of non-exclusive disordered multi-states, has been introduced already. Traders can stock 6 major brands of coffee (Maxwell House, Mellow Birds, Nescafe, etc). Only brand 2 is stocked by shop 1, whereas shop 2 stocks brands 2 and 4.

Table 1.1

Example: The Classification of Shops

Shops	Qualitatives				Disordered multi-states	Non-exclusive disordered multi-states	Ordered multi-states	Numeric
	car parking	staff helpful	deli counter	frozen foods	functional type	brands of coffee	scaled level of cleanliness	turnover
i	poor=1	yes=1	yes=1	yes=1	states(7)	states(6)	states(5)	£'000
1	1	0	1	1	4	2	5	15
2	1	0	0	1	3	2,4	5	17
3	1	1	1	0	4	3	3	22
4	0	1	1	1	2	2,4,5	1	20
5	0	1	0	0	7	4	2	31
6	0	1	1	0	5	3,6	3	34
7	0	1	0	0	5	2	2	35

An ordered attribute is defined when customers are asked to state the level of cleanliness in shops on a 5-point scale, this ranges from high quality to low quality. Finally, a single numeric attribute is specified: retail turnover is expressed in thousand pounds.

1.2.2 Primary Division

A monothetic strategy is chosen for the primary division of individuals into groups. The rationale for doing this is to facilitate rapid convergence: the optimum monothetic division should be nearer the final solution than a purely random division of individuals.

The monothetic strategy builds upon a mixed-data analogue to association analysis. All possible 2 * 2 contingency tables between pairs of attributes are created. For every pair, an inter-attribute correlation coefficient is found. Coefficients are employed as decision functions. Primary division is made using the attribute that records the highest decision function.

Construction of 2 * 2 contingency tables is straight-forward for qualitative attributes and multi-states. Take the first three binary attributes of table 1.1 (ie. poor car parking, helpful staff, and delicatessen counter). We wish to determine which is the primary attribute and then allocate the 7 shops accordingly. The number of individual shops N is 7 and the three binary attributes are labelled 1, 2 and 3 respectively.

shops i	qualitives 1	2	3
1	1	0	1
2	1	0	0
3	1	1	1
4	0	1	1
5	0	1	0
6	0	1	1
7	0	1	0

A chi-square coefficient for the 2 * 2 contingency table of two attributes j and l is:

$$\chi^2_{jl} = \frac{(ad - bc)^2 \; N}{(a + b)(a + c)(b + d)(c + d)}$$

where a,b,c and d are cell counts of the contingency table.

From the data and chi-square equation all inter-attribute correlation coefficients are calculated:

att 1 \ att 2	1	0	
1	1	2	3
0	4	0	4
	5	2	7

att 1 \ att 3	1	0	
1	2	1	3
0	2	2	4
	4	3	7

att 2 \ att 3	1	0	
1	3	2	5
0	1	1	2
	4	3	7

$$\chi^2_{12} = 3.73 \qquad \chi^2_{13} = 0.19 \qquad \chi^2_{23} = 0.06$$

To find the optimum attribute a decision criterion is needed and conventionally the maximum value of $\sum_{j \neq 1} \chi^2_{j1}$ is chosen. Thus:

Attribute 1 = 3.92
Attribute 2 = 3.79
Attribute 3 = 0.25

The maximum is attribute 1, this appertains to poor car parking facilities. Using this optimal attribute, all shops are divided into two initial groups: those shops which are inconveniently placed with respect to parking facilities and those that are not. There are 3 shops in the first group and 4 shops in the second group.

Group 1 = {1,2,3} $\qquad N_1 = 3$
Group 2 = {4,5,6,7} $\qquad N_2 = 4$

During primary division numeric attributes are dichotomised at the mean and then treated as qualitatives. Such a procedure is unsatisfactory and goes some way to explain why mixed-data analogues to association analysis are unsuccessful. In TAXON algorithms the treatment of numeric data is less of a problem; once the primary division is complete all quantitative features of the data are restored.

1.2.3 Reallocation Between Two Groups

After primary division of the data into two groups the consistency between individuals and other attributes is assessed. Where necessary, individuals are reallocated between the two initial groups.

Numeric attributes are simpler to handle, so we confine ourselves to these. A parameter P_{1j} is defined for the j^{th} numeric attribute in group 1:

$$P_{1j} = \Sigma\, x_{ij} / N_1 \qquad \Sigma \text{ for all } i \text{ in } 1$$

where N_1 is the number of individuals in group 1 and x_{ij} is the value of the jth attribute of the i^{th} individual. Given that the summation is over all i individuals in group 1, then P_{1j} is the mean value of the jth attribute for all individuals in group 1.

Primary division has placed 3 shops in group 1 and 4 shops in group 2, now we assess this grouping against numeric values for retail turnover.

shops i	primary attribute group - 1 or 2	numeric attribute turnover $j = 1$
1	1	15
2	1	17
3	1	22
4	2	20
5	2	31
6	2	34
7	2	35

While turnover was not invoked for primary division it appears to be fairly compatible with the initial division: poor parking goes with low turnover, and good parking goes with high turnover. There are two cases - shops 3 and 4 - whose positions are more ambiguous and where reallocation is a distinct possibility. Such a situation is common in practice.

Parameters are calculated for both groups:

$$P_{1j} = \Sigma\, x_{ij} \,/\, N_1 = (15 + 17 + 22) \,/\, 3 = 18$$
$$P_{2j} = \Sigma\, x_{ij} \,/\, N_2 = (20 + 31 + 34 + 35) \,/\, 4 = 30$$

To assess the allocation of shops to groups, values of P_{1j} and P_{2j} are notionally adjusted by the successive removal of the i^{th} individual. Parameters now represent mean values of the j^{th} attribute for all members of a group except individual i. Adjusted parameters are used as measures of similarity:

$$d_{1i} = \sum_i \frac{|x_{ij} - P_{1j}|}{|x_{ij}| + |P_{1j}|} \qquad d_{2i} = \sum_i \frac{|x_{ij} - P_{2j}|}{|x_{ij}| + |P_{2j}|}$$

where d is a measure of similarity based on the Canberra metric. The Canberra metric is a 'city block' or 'Manhatten' measure of similarity rather than a Euclidean or information-based measure.

Since our illustration only includes one numeric attribute the summation over j can be dropped. In practice there will be other numeric attributes to denote sales area, number of employees, and so forth. For the first shop, adjusted P_{1j} is $(17 + 22) / 2 = 19.5$ and P_{2j} remains unaltered (shop 1 does not contribute to P_{2j}). The appropriate measures of similarity are:

$$d_{11} = \sum_1 \frac{|15 - 19.5|}{|15| + |19.5|} = 0.13$$

$$d_{21} = \sum_1 \frac{|15 - 30|}{|15| + |30|} = 0.33$$

A comparison of d_{11} against d_{12} shows that shop 1 is more like group 1 than group 2 - which is the status quo. The first shop does not need to be reallocated, but some of the borderline cases do have to be shifted.

The complete set of similarity measures are tabulated below.

shops i	Canberra measures d_{1i}	d_{2i}	Interpretation
1	.13	.33	group 1
2	.04	.28	group 1
3	.16	.15	group 2 (shift)
4	.05	.25	group 1 (shift)
5	.27	.02	group 2
6	.31	.08	group 2
7	.32	.11	group 2

In most instances i remains in the same group; however assessment against the new attribute results in shops 3 and 4 swapping their allegiance. The new sets are:

Group 1 $= \{1,2,4\}$ $\quad N_1 = 3$

Group 2 $= \{3,5,6,7\}$ $\quad N_2 = 4$

Nominal attributes are approached in a fairly similar way. A Jaccard measure of similarity is used in place of the Canberra metric.

1.2.4 Secondary Division

If the desired number of groups is more than 2, the next issue is that of secondary division. One of the first two groups has to be split in order to gain three groups. A value obtained when reallocation has finished is used as a splitting rule. Reallocation will finish when all individuals have been compared against all attributes (this occurs after several cycles) and once this has happened the homogeneity of each group is assessed. The group with least homogeneity becomes the candidate for further division.

Homogeneity is calculated from Canberra-Jaccard similarity measures. If shop 1, after reallocation, is in group 1 the associated value of d_{1i} starts a running total. If shop 2 is in group 1 its value of d_{1i} is added to the running total. Totals for all d_{1i} and d_{2i} are divided by the number of individual shops in the new groups (N_1 and N_2 respectively).

$$D_1 = (\sum_i d_{1i}) / N_1 \qquad D_2 = (\sum_i d_{2i}) / N_2$$

Terms for D are measures of homogeneity. The term with least homogeneity (highest value of D) is divided next.

If the only two attributes in a classification are for car parks and retail turnover, then values from section 1.2.3 can be taken to find the sum of d_{1i} and d_{2i}, and each sum will be divided by $N_1 = 3$ or $N_2 = 4$ shops.

$$D_1 = (.13 + .04 + .05) / 3 = 0.07$$
$$D_2 = (.15 + .02 + .08 + .11) / 4 = 0.09$$

Group 2 is the least homogeneous, so further division of the data is in terms of group 2.

1.2.5 Reallocation Between All Groups

Convergence tends to be quite rapid. Once a final division of the data has been made most algorithms stop, this is especially true of algorithms employed in biological taxonomy. The hierarchical structure of groups (the dendogram) is of particular interest in biological work. Whereas,in geographical analysis,the route by which data are classified is rarely meaningful, and attention turns to the fine-tuning of group membership.

The procedure for reallocation between K final groups involves a straight forward extension of those outlined in section 1.2.3. Only the number of comparisons increases and no new principles are invoked.

1.2.6 Assessment of Each Attribute

Successful classification provides a set of solutions for 2,3,4,...,K groups. Required now is a way to assess the contribution of individual attributes and a way to decide upon the optimum number of groups. In both instances reference is made to what Ratkowsky and Lance (1978) have called 'the Cramer criterion'. The Cramer criterion is recommended because it lies within the bounds zero and one, and is consistent across all types of attribute.

The contribution of each attribute to the final classification is considered first. Precisely how each attribute is assessed depends on its type: whether nominal or numeric.

Nominal attributes are reported as contingency tables, for which conventional χ^2 statistics measure the degree of inter-cell association. The contribution of an attribute, when data are classified into K groups, is

$$C = \left[\frac{\chi^2 / N}{\min(s-1,K-1)}\right]^{\frac{1}{2}}$$

where N is the total number of individuals and min(s-1,K-1) signifies the smaller of two quantities s-1 and K-1. Consider the attribute for frozen foods and let N=7 shops and χ^2=4. Classification into two groups (K=2) gives a value for C of:

$$C = \left[(4/7) / (2-1)\right]^{\frac{1}{2}} = 0.8$$

On a scale from one to zero the attribute for frozen foods scores 0.8.

Numeric attributes are treated using principles familiar from the analysis of variance. If B is the between-group sum of squares and T the total sum of squares, then $(B/T)^{\frac{1}{2}}$ is a measure of the contribution of an attribute. After reallocation, to take one example, the continuous attribute for retail turnover has between-group sum of squares of just over 3.8 thousand and total sum of squares of 4.7 thousand. The C value is:

$$C = (3.8/4.7)^{\frac{1}{2}} = 0.9$$

On a scale from one to zero the attribute denoting store turnover scores 0.9.

These Cramer values provide a way to rank attributes and to isolate the most significant aspects of the data. Mean Cramer values - calculated from all attributes - serve as norms. Values which exceed the mean are significant. A stricter condition is imposed on the results that are presented later; to be significant individual Cramer values must exceed one standard deviation above the mean. While these tests have the appearance of formality (ie. one standard deviation above the mean lies at a point representing 68% of the area under the normal curve) no formal inferences should be drawn.

1.2.7 Optimal Number of Groups

Mean Cramer values, the norms just calculated from all attributes, are used to determine the optimal number of groups. We note that mean values rise as the number of groups increases, but the rate of increase is smaller on each occasion. A typical set of mean Cramer values might be 0.17 for 2 groups, 0.3 for 3 groups, and 0.35 for 4 groups. There is no obvious stopping point in this series; however, a single optimum is available if each mean (0.17, 0.3, ...) is adjusted by the number of groups corresponding to that mean.

Ratkowsky and Lance (1978) suggest the term:

$$\text{Scaled C} = \overline{C} / K^{\frac{1}{2}}$$

where $\overline{C}$ is the mean Cramer value when there are K groups. The optimum number of groups is found when Scaled C is at a maximum. Scaling is analogous to taking account of regression degrees of freedom. But there is no formal inferential basis for the assessment of Cramer values and the fractional positive power $K^{\frac{1}{2}}$ is chosen simply for its good empirical performance.

Now it is possible to find the optimal number of groups given data about shops and their characteristics. Two Cramer values for each number of groups are presented below:

Number of Groups K	Mean Cramer Values $\overline{C}$	Scaled Cramer Values $\overline{C} / K^{\frac{1}{2}}$
2	.17	.12
3	.30	.17
4	.35	.18
5	.38	.17
6	.40	.16

The series of scaled Cramer values descibes an inverted U shape which peaks at .18, corresponding to a 4 group solution. This might be a reasonable outcome for the classification of over 1,000 shops in Cardiff. Groups of shops might be descibed as 'small and friendly', 'large and good value for money', 'cheap and impersonal', and 'expensive and good quality'.

In the sections that follow the comments made above are amplified and substantive results are presented.

2 Classification of Consumer Activity

Applications which are of substantive interest are set forth in this section and the next. Consideration is given to several aspects of polythetic division, including the purpose, definition of attributes, division and reallocation, interpretation, the optimal number of groups and computation. A major distinction is drawn between principal trips and all trips. All examples are confined to one week in the first instance; later,data from subsequent weeks are introduced in order to assess the validity of classification.

2.1 The Purpose

The main aim is to classify shopping trips into a small set of bundles, or patterns, from information contained in several attributes. Homogeneity is optimised so that within a bundle all types of activity are similar. The definition of bundles enables us to identify major themes in the data and to isolate the most important associations between individuals, their movements and their shopping behaviour. The bundles are summaries of complex data; they are not natural groups, but at a later stage they may be incorporated within formal models.

Sets of attributes are defined for two types of trip, namely principal and all trips. Principal trips occur where expenditure is highest; generally these involve a strong commitment, heavy buying and lengthy travel. Often coupling constraints have to be met because the whole family participates and the family car is used. The collection of all trips has principal trips as a subset, also included are minor 'topping up' visits. The separation of major expeditions from other trips is fairly familiar (indeed most surveys only consider major expeditions).

2.2 Attributes

The complete set of attributes remains the same for both principal trips and all trips, although the percentage in each category varies (ie. local buses might be caught on 5% of principal trips, rising to 15% of all trips).

There are 19 attributes in total: 6 qualitatives, 7 disordered multi-states, 4 ordered multi-states and 2 numerals. For convenience the full list of attributes is laid out in table 2.1, against each acronymn is a brief description and, where relevant, the number of states is mentioned. These cover the full range of influences: from relevant descriptions of the shopper (car ownership, location of home, work status), to forms of movement (means of travel, whether multi-stage), and the importance of a trip (expenditure, items bought) and the context in which trips are made (time of purchase, surrounding activities, location of centres).

Table 2.1

Attributes for the Classification of Shopping Trips

Acronymns	Attributes	States
	Qualitatives = 6	
CAR	Whether car is available for shopping	2
DEPFRE	Whether separate deep-freezer is owned	2
MARITAL	Whether shopper is married	2
MULTI	Whether trip is multi-staged	2
EVENING	Whether trip occurs during early evening	2
FROZEN	Whether bulky frozen goods are bought	2
	Disordered Multi-States = 7	
HLOCAT	Location of home	8
PACT	Previous activity	6
DAY	Day of week	7
MODE	Mode of travel to shops	5
LOCAT	Type of shop location	5
SACT	Subsequent activity	6
GOODS	Non-exclusive product groups	9
	Ordered Multi-States = 4	
AGE	Age of shopper	7
WORK	Working status of shopper	3
SIZE	Size of household	6
TIME	Time of shop visit	6
	Numerals = 2	
EXPEND	Expenditure on listed grocery goods	-
ITEMS	Number of product fields	-
	Total Attributes = 19	

(a) Qualitatives

Qualitatives are 6 in number. These define the presence/absence of a feature. A distinction is drawn between characteristics of the shopper or household, and characteristics of the trip. Possession of a deep-freezer, denoted DEPFRE, is indicated by about 45% of the sample. About two-thirds say that a car is available for shopping, attribute CAR captures this effect. Both these attributes influence the quantity of goods that can be purchased, carried home and stored. The third characteristic of the shopper, MARITAL, is a binary indicator of whether the shopper is married.

Characteristics of the trip are described by attributes MULTI, EVENING and FROZEN; these denote whether the shopping trip is multi-staged, whether it takes place during the early evening, and whether frozen goods are purchased. More than one shop is visited on 42% of principal trips, and these are defined as multi-staged. Because frozen meat and poultry are bulky and invariably sold at specialist outlets these are kept apart from references to other goods. Further binary attributes for a variety of product groups are not defined because these would give too much weight to the goods purchased.

(b) Disordered multi-states

Only one of the 7 disordered multi-states refers to households. The shopper's home is in one of 8 study areas, each of which is a state. Descriptive analysis has shown that many trips do not start from home, so to indicate which previous activity was undertaken the attribute PACT is defined.

The journey is made on a particular DAY (7 states) by travelling on a MODE (5 states). Destinations, LOCAT, are represented by 5 types of shop location: city centre, district centres, local centres, individual and mobile shops, and satellites outside Cardiff. Further refinement of the destination attribute is possible, although the number of states is limited for computational reasons. Activity after the shop visit is represented by the attribute SACT, this has 6 states.

A single non-exclusive multi-state is included in the exercises. Shoppers may buy GOODS from several product fields; the order in which goods are bought is immaterial but the ability to buy from several product fields means that decisions are non-exclusive. Thus, cleaning agents from one product field and beverages from another may be bought on the same occasion. A coarse mesh of only 9 states is defined (cleaning agents, breads, canned goods, and so on).

(c) Ordered multi-states

The order in which states are arranged is deemed to be important. Three characteristics of the shopper are defined: AGE divides into 7 states; work status, WORK, comprises 3 states; and, with 6 states, SIZE denotes household size (over half the households have either 2 or 4 members).

Time of purchase, TIME, is introduced as a fourth ordered multi-state. There are 6 states, starting with 6% of principal trips before 10 am and ending with 5% after 6 pm.

(d) Numerals

Most social survey data is categorical and data contained in consumer panels are no exception, therefore very few numeric attributes are defined. Expenditure on grocery goods is the only true numeric attribute. EXPEND expresses the amount spent (in pounds); mean expenditure is £12, and upper and lower quartiles are £16 and £5 respectively. Another quasi-numeric attribute is derived from the list of 68 product fields. Across all shopping occasions goods are bought from a mean of 15 product fields. Upper and lower quartiles lie at 22 and 7 respectively.

All attribute types can cope with missing data. In practice only a few attributes - TIME and PACT for instance - actually have missing entries. Algorithms DATX and PARAMS receive and check the data to ensure that values are within valid bounds and that states are correct.

2.3 <u>Results for Principal Trips</u>

<u>Example 1</u> <u>Principal Trip Patterns in One Week</u>

2.3.1 Division and Reallocation

Principal trips, numbering 445 in one week, are divided by the most discriminating monothetic solution into two groups. Some 6 panellists did not record any trips during the week under study (because they were away or they shop every other week), so the number of principal trips is 445. The numeric attribute ITEMS is the most discriminating attribute, and it gives an initial split into two unequal-sized groups of 205 and 240 trips. In this initial solution the homogeneity value is 0.64 (measured on a scale from 1 to 0 and where lower values are more homogeneous), and an improvement is sought.

Following the initial solution, the allocation of trips to groups is reassessed against new attributes. Eventually the homogeneity value falls to 0.62; this improvement occurs after a net movement of 52 cases. Given that each panellist makes one principal trip per week, there are now 257 and 188 trips in the two groups.

After two homogeneous groups have been derived it is possible to fine-tune the result. A further algorithm is called (REMUL) to see whether the data can be partitioned any better. The purpose of this additional algorithm is to enable movement between any of the groups; such an option becomes more important as more groups are defined. The result is a net shift of 5 cases.

Overall, a substantial change takes place in group membership. The number of shopping trips in each group is summarised below:

Group	Group Membership		
	initial DIPCAN	final DIPCAN	final RECAN
1	205	257	252
2	240	188	193

A monothetic result corresponds to that shown under initial DIPCAN. Monothetic association analysis would generate such an imperfect result. Hierarchical divisive approaches stop at final DIPCAN, and at this stage the dendogram can be extracted.

2.3.2 Interpretation of Attributes

Once the final reallocation has been made the importance of each attribute is ascertained. Cramer values are used for this purpose. More important attributes score higher values on the Cramer scale. The mean Cramer value among 19 attributes is 0.31 and critical values are defined at ± 1 standard deviation either side of the mean (ie. at 0.45 and 0.17). With a value of 0.64 the attribute MODE is definitely most significant, whereas the non-exclusive multi-state for GOODS has a value of 0.07 and adds nothing to the classification. ITEMS, the most discriminating attribute initially, is fifth now that a final reallocation has been performed.

Two attributes - MODE and CAR - are significant and three attributes are insignificant - PACT, FROZEN and GOODS. Trips appear to be distinguished by the form of travel rather than by what shoppers purchase.

To illustrate the type of information that is available consider the qualitative attribute CAR and the continuous measure EXPEND; these have individual Cramer values of 0.58 and 0.37 respectively.

The attribute CAR indicates whether a car is available for shopping on the principal trip. There are two states. The contribution of this attribute to the classification of 445 principal shopping trips (ie. one per panellist) is:

	Car unavailable	Car available	Total
Bundle 1	31	221	252
Bundle 2	132	61	193
Total	163	282	445

Out of 252 trips allocated to bundle 1, 88% are undertaken by shoppers who have access to a car; conversely only 32% of trips in bundle 2 are characterised in the same way. A χ^2_1 value of 148 exceeds tabulated χ^2_1 by a considerable margin, and it is concluded that the degree to which a car is available significantly discriminates between the two bundles.

EXPEND is a numeric attribute, measured in pounds, which has a mean of just over £12. For members of bundle 1 the mean approaches £16, whilst for members of bundle 2 mean expenditure is below £8. Division is into groups of high and low expenditure. Analysis of variance confirms that the groups are internally homogeneous and with $F_{1,443} = 71$ expenditure differences between the two bundles are significant.

Inspection of attributes enables us to interpret the major features of each bundle and to distinguish typical patterns. The following features are noted for the 2-bundle solution and are sketched in figure 2.1.

(a) Bundle 1 N = 252

These principal trips are undertaken by shoppers who have access to, and use, a car. Expenditure is heavy and goods are selected from a wide range of product fields. Most consumers travel from the wealthier suburbs of Cardiff to district centres and out-of-town superstores, often on Thursday and Friday evenings and certainly sometime over the period Thursday to Saturday. Typically only one shop is visited for grocery goods. Shoppers are married and live in large households.

(b) Bundle 2 N = 193

Invariably no car is available, so the typical pattern involves walking to several shops within a district centre. Expenditure is light and only a moderate number of product fields are selected. Fridays are popular - during the daytime - and the number of other weekday trips is significant too. Most shoppers live in small households and a large proportion are unmarried.

2.3.3 Selection of Groups

Two groups have been identified, now we need to ascertain whether further groups can be distinguished, whilst always bearing in mind that only the most discriminating features of the data are of interest.

Recall that the final allocation from DIPCAN left 257 trips in group 1 and 188 in group 2; it is at this point that further groups can be defined. If 3 activity bundles are required then the least homogeneous group is divided (group 1 in this instance). In fact the difference in homogeneity values between groups 1 and 2 is slight, which suggests that further division could be sensitive to slight variations in group membership and attributes. An investigation of validity, done in section 3, clarifies this issue.

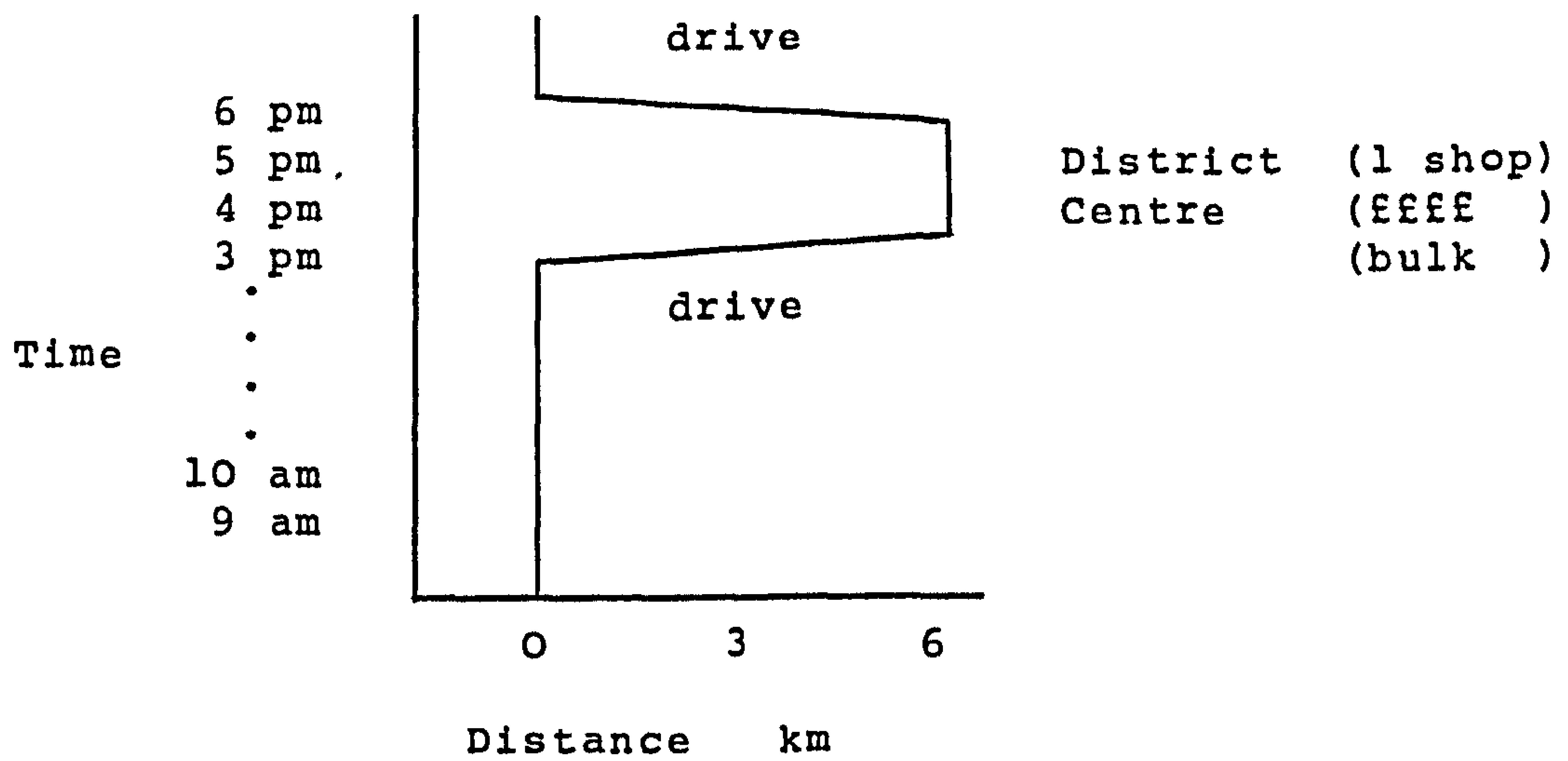
Further division into K groups is undertaken and at each stage homogeneity improves in the usual way. A final reallocation between groups (RECAN) allows partitions to be improved. Now that more than 2 groups are defined this final stage assumes a greater role; gross changes are fairly extensive and many trip patterns are reallocated among the K-bundle solutions.

At the completion of each division, for 2,3,...,K bundles,

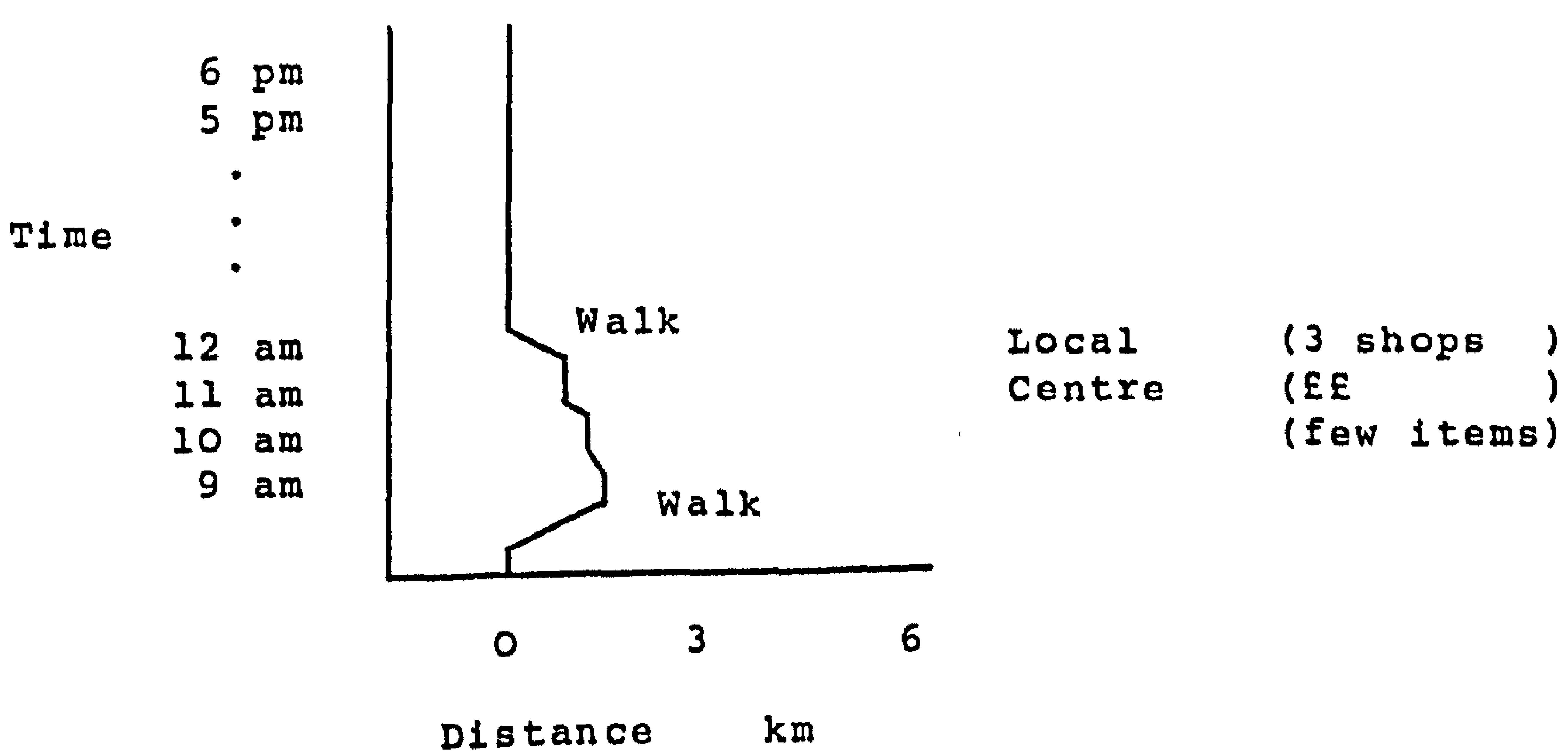
Figure 2.1

Interpretation of the 2-Bundle Classification of Principal Trips: A Sketch

Individual Path in Bundle 1: Suburban Home



Individual Path in Bundle 2: Inner City Home



Cramer values are calculated. Scaled values reveal a single peak which corresponds to the optimal number of groups. Results are:

Number of Groups	Scaled Cramer Values
2	0.22
3	0.20
4	0.17

Highest of the scaled Cramer values is 0.22,therefore the 2-group solution is accepted as the optimal division of trips based upon 19 attributes.

While the 2-bundle solution is optimal it is instructive to compare results for slightly more divisions than this, so most results presented here cover 2,3 and 4 group solutions. Rank orders for the 19 attributes are presented in table 2.2, where attributes are arranged in descending order given by the 2-bundle solution. Generally, the same discriminating attributes remain important and the same insignificant attributes remain unimportant.

There are some notable deviations: DAY of week fails to make any sizable contribution to the definition of 3 and 4 bundles, while MULTI suddenly becomes very important indeed when 4 bundles are defined. Consistently important are indicators of travel (MODE and CAR), and measures of the quantity bought (EXPEND and ITEMS). Most consistent of all is the failure of GOODS to contribute anything. What actually is bought on a trip does not influence trip-making behaviour.

The main features of these additional bundles are described. For 3-bundles:

(a) Bundle 1 N = 192

A pattern of bulk-purchasing is observed. Only one shop is visited on each principal trip and most likely this will be in a district centre or out-of-town superstore. Expenditure is heavy and goods are obtained from many product fields. Often a car is available for shopping but it is not always used.

(b) Bundle 2 N = 181

For moderate expenditure a wide number of goods are purchased, often from several different grocery shops within a district centre. Shoppers walk.

(c) Bundle 3 N = 72

Wealthy shoppers living in the northern suburbs use a car to purchase relatively few items, at moderate expenditure, in local centres. There is a mixture of single-stage and multi-stage trips. Most occur during the day and some are associated with workplace activities. Some shoppers will alternate between this pattern of low-commitment activity one week and bulk-purchasing behaviour the week after.

Table 2.2

The Comparative Importance of Attributes:
Classification of Shopping Trips into 2, 3 and 4 Bundles

Attributes	Rank of Attributes, Week 1 (Ordered by the 2 bundle classification)		
	2 Bundles	3 Bundles	4 Bundles
MODE	1	3	7
CAR	2	1	3
MARITAL	3	9	5
EXPEND	4	5	4
ITEMS	5	2	2
DAY	6	16	17
HLOCAT	7	6	10
EVENING	8	8	8
SIZE	9	14	11
MULTI	10	10	1
LOCAT	11	4	9
AGE	12	13	12
SACT	13	7	6
TIME	14	18	18
DEPFRE	15	12	14
WORK	16	15	15
PACT	17	11	13
FROZEN	18	17	16
GOODS	19	19	19

The features of 4 bundles are:

(a) Bundle 1 N = 180

Bulk purchasing behaviour is revealed by those shoppers who are predominantly married and have access to a car. Expenditure is heavy and goods are purchased from a large number of product fields. Most trips are destined for district centres, sometimes in the evening.

(b) Bundle 2 N = 108

Expenditure is fairly heavy and a moderate number of goods are bought, despite most trips being made on foot. Local centres dominate, which allows many grocery shops to be visited on a single trip.

(c) Bundle 3 N = 96

Expenditure and the range of goods bought are both low. A variety of district centres are reached, mainly by foot or bus. Only one shop is visited on each trip.

(d) Bundle 4 N = 61

Invariably a car is used to reach one or more shops. These are located in district, local and satellite centres. Goods are selected from few product fields and at moderate expenditure. Shopping trips are a mixture of single-stage and multi-stage visits which terminate at home.

The composition of each bundle is detailed in tables 2.3 to 2.5. Attributes, whose individual Cramer values exceed the mean, are presented in rank order; in table 2.3, for example, the most important attribute is MODE and this distinguishes between 71% of trips where a car is used (bundle 1) and 73% where shops are reached on foot (bundle 2).

Generally unimportant are attributes associated with the goods bought and with the socio-demographic features of shoppers (such as age, deep freezer ownership, work status) - unless HLOCAT is regarded as a loose proxy for socio-economic variables. It might be expected, for instance, that there is an association between the purchase of bulky goods, car-borne trips, superstores and working shoppers; or that the purchase of breads and fresh foods, especially by non-working shoppers, is associated with localised shopping during the morning. These expected associations between goods, shoppers and activities are not supported by the classifications.

The conclusion to emerge is that trips are differentiated by travel to reach shops and by the quantities bought, precisely what is bought and by whom is relatively unimportant.

Table 2.3

Principal Trips: Interpretation of the 2 Bundle Classification, Week 1

Attributes	Interpretation: Bundle 1, N = 252	Interpretation: Bundle 2, N = 193
MODE	71% car	73% walk
CAR	car available to 88%	car unavailable to 68%
MARITAL	94% married	36% unmarried
EXPEND	heavy £16	light £8
ITEMS	18 items	11 items
DAY	mode is Thursday 33%, 50% on Friday and Saturday	mode is Friday 31%, 29% on Tuesday and Wednesday
HLOCAT	from wealthier suburbs: 26% Rhiwbina, 13% Llanedeyrn and Heath	from Rumney 20% and Llanrumney 19%
EVENING	often Thursday and Friday evening	rarely Thursday or Friday evening
SIZE	34% 4-member households, 18% have 5 members	30% 2-member households, 24% have 3 members
MULTI	72% single-stage	60% multi-stage
LOCAT	moderate patronage of district centres 45%, also out-of-town superstores	dominated by district centres

Included are those attributes which have individual Cramer values in excess of the mean.
Differences between bundles are significant at 99%

Table 2.4

Principal Trips: Interpretation of the 3 Bundle Classification, Week 1

Attributes	Interpretation		
	Bundle 1, N = 192	Bundle 2, N = 181	Bundle 3, N = 72
CAR	car available to 83%	71% without car	car available to 97%
ITEMS	21 items	12 items	8 items
MODE	66% car	72% walk	70% car
LOCAT	55% district centres 28% free-standing	73% district centres	49% local centres
EXPEND	£17 - heavy	£8 - light	£9
HLOCAT	Cathays, otherwise even spread	20% in each of Rumney and Llanrumney	56% Rhiwbina, 18% Heath
SACT	69% home	51% other shop	more even, 14% work
EVENING	evenings fairly important	wholly daytime	virtually all daytime
MARITAL	majority married	some single	mainly married
MULTI	78% single-stage	59% multi-stage	even split

Included are those attributes which have individual Cramer values in excess of the mean.
Differences between bundles are significant at 99%.

Table 2.5

Principal Trips: Interpretation of the 4 Bundle Classification, Week 1

Attribute	Interpretation			
	Bundle 1, N = 180	Bundle 2, N = 108	Bundle 3, N = 96	Bundle 4, N = 61
MULTI	79% single-stage	96% multi-stage	84% single-stage	even mixture
ITEMS	22 items - many	14 items	9 items	8 items - few
CAR	84% car availability	60% without car	71% without car	98% car availability
EXPEND	£18 - high	£10	£6 low	£10
MARITAL	93% married	some single	even split	97% married
SACT	70% home, 11% other place	82% other shop	78% home	even across categories
MODE	68% car	73% walk	69% walk, 21% bus	78% car
EVENING	important	daytime	daytime	daytime

Included are those attributes which have individual Cramer values in excess of the mean.
Differences between bundles are significant at 99%.

2.4 Results for All Trips

Example 2 All Trip Patterns in One Week

2.4.1 Division and Reallocation

Most shoppers in Cardiff make between 2 and 6 trips to grocery outlets each week. Every trip is described by the set of attributes defined in section 2.2. Polythetic division splits these trips, about 2200 across all consumers in a typical week, into two groups. The initial split is generated by the measure of previous activity PACT which results in 2134 cases allocated to group 1 and 74 allocated to group 2. This initial split is a monothetic division akin to association analysis; the groups are very unbalanced and of little utility.

Results from the initial solution are used as input to the polythetic division, at the end of which group 1 has 1377 members and group 2 has 831. Once the main division has been completed further reallocation is permitted to improve the homogeneity of groups and a net shift of 24 trips occurs.

The shift towards a balanced division is summarised below:

Group	Group Membership		
	initial DIPCAN	final DIPCAN	final RECAN
1	2134	1377	1353
2	74	831	855

There is a huge difference between the initial monothetic solution and the final polythetic division (after reallocation), as a consequence serious doubt must be cast on results gleaned from association analysis alone. Differences between methods which preserve the hierarchy and those which do not are less fundamental. Where the dendogram is of substantive interest and where computational costs are to be minimised the result before final reallocation may be acceptable, even if its partitions are not optimal.

2.4.2 Interpretation of Attributes

The mean Cramer value for 19 attributes is 0.26 and 4 attributes lie one standard deviation above the mean. Most important is LOCAT which has an individual Cramer value of 0.62, this is followed by HLOCAT, MODE and CAR (see definitions in table 2.1). Location and travel mode dominate the picture, ie. when all trips are considered the most discriminating attributes refer to the consumer's home location, the location of shops, car availability and the vehicle actually used to reach shops.

At the other end of the scale, GOODS and FROZEN remain as insignificant for the classification of all trips as they were for principal trips, both their Cramer values are 0.09.

This information is brought together to define the profile of each bundle:

(a) Bundle 1 N = 1353

Most shoppers walk to district centres nearest their suburban homes. Some trips are multi-staged and combine with other activities, including work. Such behaviour is observed for all types of consumer, irrespective of socio-economic position, age or household size.

(b) Bundle 2 N = 855

While a car is available to most shoppers, it is only used 50% of the time. Large numbers of local shops are visited, but superstores are an important element too. This pattern of activity is most evident in prosperous areas and most trips are single-staged visits from these residential zones.

The main distinction contained in this division of all trips is between the 'steady shopper' defined in bundle 1 and the'peaky shopper' of bundle 2; periodically, the latter undertakes major shopping trips by car, at other times local shops are visited to 'top up' on fresh foods and perishable goods.

2.4.3 Selection of Groups

Two groups have been identified, now we need to check whether further groups stand out.

The final polythetic allocation from DIPCAN left 1377 and 831 in each of the groups. To obtain a third group the least homogeneous group is split. Decision functions for groups 1 and 2 are 0.32 and 0.33 respectively, so the latter is split. Partitioning group 2 has some intuitive appeal since it contains both major and mundane trips. A 4-group solution is attempted too.

Scaled Cramer values for these solutions are:

Number of Groups	Scaled Cramer Values
2	0.18
3	0.16
4	0.15

Values peak at 0.18, therefore the 2-group solution is optimal. Other K-group solutions might provide supplementary information.

Where the division is three-fold (table 2.7) the profile of bundles can be described in the following manner:

(a) Bundle 1 N = 868

These are single-stage trips which flow into district centres. Most movements are pedestrian and the number of purchases on each occasion is small. Store choice appears to be confined to localities around the home and quantities purchased are limited by carriage constraints.

(b) Bundle 2 N = 823

Half of these trips are multi-stage; the majority are destined for district centres where several shops can be patronised at the same time. Goods are bought from roughly 10 product fields for an average expenditure of £6. Consumers mainly originate from the east side of Cardiff (ie. Llanrumney, Llanedeyrn and Rumney).

(c) Bundle 3 N = 517

These are car-borne, single-stage trips, many of which originate from wealthier suburban areas such as Rhiwbina and Heath. Purchasing levels and expenditure per trip are high, in contrast to the features of bundle 1. Unlike the two other bundles, the trips in bundle 3 are quite likely to be destined for the city centre, free-standing stores and local shops (ie. the effective range of shopping opportunities is much wider and the movement of consumers appears to be much freer).

Many of these features are repeated when we interpret the 4-bundle solution (table 2.8):

(a) Bundle 1 N = 805

Like bundle 1 of the three-fold division, trips are single-stage, low-purchase, and home-oriented events. Some 79% of trips are walked and a further 13% involve public transport. It appears that these spatially constrained movements are mainly associated with residents living in Rumney and Llanrumney.

(b) Bundle 2 N = 521

Trips are multi-stage and over half are walked, yet a large number of items are purchased. District centres are the principal destinations. Most consumers who exhibit this pattern of movement do not possess a deep freezer, and this fact might account for the absence of bulk-purchase buying.

(c) Bundle 3 N = 483

These are low commitment single-stage trips. Often a car is available but it is not always used: the number of purchases is so few and movement is so localised that car travel is unwarranted. 'Topping up' visits and short trips to purchase perishable foods (milk, bread, fruit, etc) would come under this category.

(d) Bundle 4 N = 399

Again these are single-stage events; but,unlike bundle three,car travel from wealthier areas such as Rhiwbina and Heath dominates the picture. More goods are bought: 7 items for an outlay of £7 on average. More than half the consumers who display this pattern of behaviour own a deep freezer, so bulk-purchasing is a feasible option. Like bundle 3 of the three-fold division, the effective range of shopping opportunities is wide, even to the extent that 6% of trips are destined for satellite centres (for example the Carrefour at Caerphilly).

Comparison of all three solutions shows that the shop location, LOCAT, is something of an aberration: it is important in the definition of 2 bundles, yet never is it as significant again. The attribute for multi-stages, MULTI, comes to dominate the picture, which implies that single-stage trips are very different from multi-stage trips, and that among single-stage trips walking and car travel makes a tremendous difference.

In summary, the set of all trips is divided by location factors, travel mode and the number of stages; precisely what is bought and by whom is relatively unimportant.

At this stage it is useful to draw some comparisons between the classification of principal trips and all trips:

(1) Use of car is an important discriminator of principal trips: those consumers whose behaviour is characterised by bundle 1 use a car, whereas those in bundle 2 tend to walk (table 2.3). This sharp modal split is not repeated when we consider all trips: instead we find that the majority of trips are walked, and that this is true for most types of people. Indeed, the number of stages on a trip is a better discriminator of all trips than modal split (table 2.6).

(2) As more and more bundles are defined, so the distinction between multi-stage and single-stage trips becomes more apparent, even in the case of principal trips.

(3) Attributes to denote the location of households and shopping centres are important throughout the analysis. Location factors, however, have a particularly strong effect when all trips are divided into two bundles: there is a clear distinction between trips destined for district centres and those involving a wider range of centres (including superstores).

(4) While the number of purchases always is crucial, orders of magnitude are variable. Consider the 3 bundle solution: averages range from 8 items (bundle 3) to 21 items (bundle 1) for principal trips, whereas the range is from only 2 items (bundle 1) to 10 items (bundle 2) for all trips. Thus, orders of magnitude are much lower when all trips are studied.

Table 2.6

All Trips: Interpretation of the 2 Bundle Classification, Week 1

Attribute	Interpretation	
	Bundle 1, N = 1353	Bundle 2, N = 855
LOCAT	76% to district centres	local shops 30%, also superstores
HLOCAT	20% from each of Llanrumney and Rumney	39% from Rhiwbina, 15% from Heath
MODE	71% walk	48% car, 36% walk
CAR	only 44% have car available	car available to 89%
SACT	home, also other shops	home for 62% of cases
PACT	often from work	74% from home
MULTI	37% multi-stage	91% single-stage
DEPFRE	majority have deep-freezer	61% have deep-freezer

Included are those attributes which have individual Cramer values in excess of the mean.
Differences between bundles are significant at 99%.

Table 2.7

All Trips: Interpretations of the 3 Bundle Classification, Week 1

Attribute	Interpretation		
	Bundle 1, N = 868	Bundle 2, N = 823	Bundle 3, N = 517
MULTI	97% single-stage	56% multi-stage	80% single-stage
MODE	75% walk	71% walk	81% car
ITEMS	2 items	10 items	8-9 items
EXPEND	low £2	£6	high £8
CAR	even split	even split	96% have car available
LOCAT	district centres 50%	75% to district centres	25% into city centre, 37% to local stores
HLOCAT	across all areas	mainly from east side	52% from suburban Rhiwbina
SACT	home 69%	other shop and home	majority go to home, also other places and other shops

Included are those attributes which have individual Cramer values in excess of the mean.
Differences between bundles are significant at 99%

Table 2.8

All Trips: Interpretation of the 4 Bundle Classification, Week 1

Attribute	Interpretation			
	Bundle 1, N = 805	Bundle 2, N = 521	Bundle 3, N = 483	Bundle 4, N = 399
MULTI	91% single-stage	89% multi-stage	97% single-stage	93% single-stage
CAR	70% car unavailable	67% car available	mainly car available	96% car available
SACT	72% homeward	to other shops	mainly homeward	69% home
ITEMS	6 items	10 items - many	2 items - few	7 items
MODE	79% walk, bus 13%	57% walk, 29% car	68% walk	86% car
EXPEND	£3	£7	£1-2 - light	£7
LOCAT	71% district centres	mainly district centres	40% individual shops	41% local centres, 6% to satellite towns
HLOCAT	lots from Rumney and Llanrumney	fairly even spread	non-inner city areas	mainly Rhiwbina and Heath
DEPFRE	77% without	majority without	about 60% with freezer	60% with deep freezer
MARITAL	significant number single	overwhelmingly married	mainly married	majority married

Included are those attributes which have individual
Cramer values in excess of the mean
Differences between bundles are significant at 99%

Apart from these differences there are some common factors. In fact we can conclude that for both types of trip the main division will be made in terms of location factors, travel mode and the number of stages; and that precisely what is bought and by whom is relatively unimportant.

2.5 Computation

Classification methods, quite rightly, are assessed against empirical evidence and chosen for their mathematical consistency. An attempt to do this for two large examples has been made in the previous sub-sections. In addition, however, the practitioner is interested to know about tractability and computational costs.

Little academic consideration is given to costs, yet often these are heavy and force users to adopt sub-optimal techniques. Two aspects are discussed: storage of data and computation time.

Storage of data is mentioned first. Let N be the number of individuals and J the number of attributes. An agglomerative routine needs to construct a N * N similarity matrix, and this has N(N-1)/2 unique entries which have to be stored. By contrast a divisive routine need only store the original N * J data matrix.

To illustrate the dramatic fall in storage requirements when a divisive strategy is adopted consider the case of N=440 shoppers and J=19 attributes:

Agglomerative method	about 97 thousand entries
Divisive method	about 8 thousand entries

Computation time, the second aspect to be considered, is closely related to storage requirements: it takes longer to pass through 97 thousand entries than about 8 thousand. Agglomerative routines construct a complete hierarchy involving $(N-1)^2$ calculations, most of which are redundant (since only a few joins are meaningful). Whereas divisive methods perform calculations on N individuals for the pre-specified number of groups K alone.

Consumption of computer time in divisive methods is proportional to the number of individuals N and the square of the number of attributes J. This is true for all polythetic situations, except where there is reallocation. Therefore, a large increase in the number of attributes (relative to N), and the introduction of reallocation algorithms, will reduce the comparative advantage of divisive strategies.

Central processor time spent on the ULCC Cray-1S machine is shown in table 2.9 for classification of all trips and principal trips. Polythetic division is performed on samples of about 2100 and 440 individuals respectively and in all cases K=2,3, and 4 and J=19 mixed attributes. The average execution time for principal trips is 35 seconds, this increases more than proportionately to 14 minutes 16 seconds for all trips. Reallocation does prove to be expensive when all trips are analysed, but not infeasible.

Table 2.9

CPU Time on the ULCC Cray - 1S Machine:
Polythetic Division

Week	Sample Size	Execution Time
(a) Principal Trips		
1	445	36 sec
2	442	33 sec
3	436	34 sec
4	438	35 sec
Average	440	35 sec
(b) All Trips		
1	2208	4 min 52 sec
2	2173	4 min 14 sec
3	2036	3 min 42 sec
Average	2139	4 min 16 sec

On each occasion the whole sample is classified into 2, 3 and 4 bundles using 19 attributes

3 Assessment of Classifications

Ideally the validity of all findings from classification should be tested. The impact of slight variations in data or attributes needs to be gauged: if minimal changes to the input alter partitions and change group membership our confidence in the findings is diminished. Tests include the removal of outlying patterns, the successive deletion of individual trips, and the introduction of random perturbations. Comparison of results after these modifications have had their effect indicates the validity of classification.

Researchers working in physical and biological sciences are able to repeat their investigations under experimental and simulated conditions. This makes the assessment of stability, sensitivity and overall robustness a routine matter. Rarely is this true for researchers in social science. Generally the most that can be achieved is to divide the whole into parts, and then compare classifications made on the parts. If the same structure is discovered repeatedly within the parts then the solution probably has some validity.

The longitudinal panel is one of the few sources in social science which enables replicate analysis. The parts into which data are divided - weeks - are natural and meaningful. If aggregate behaviour each week is fairly stable (not an unreasonable assumption, see section 3.4 of Chapter 1), then classifications over several weeks can be regarded as repeated 'experiments'.

Minor perturbations of the data happen each week: a few new shoppers are added, others are deleted, individual behaviour changes slightly, there are marginal variations in the noisiness of data. Because of these changes the solution alters, yet the structure remains essentially the same. Replicate analysis should reveal the same significant messages, the same salient features, and the same proportion of trips in each bundle over successive weeks.

Assessment is twofold:

(a) stability

Identical classification exercises are performed over several weeks, the results from which are compared. Comparison facilitates an evaluation of stability. Special attention is given to the stability of summary measures, major attributes and the proportions allocated to well-partitioned bundles. This is done for principal and all trips (section 3.1).

(b) sensitivity

To assess the degree of sensitivity to minor changes in the definition of attributes, principal trips are classified from a similar range of characteristics. Only minor attributes are deleted or changed, so solutions should be consistent, if not identical. In particular, summary measures should be similar and considerable overlap is expected in the membership of groups (section 3.2).

While it is unusual for there to be any replicate analysis in social science the approach adopted here is limited. No mathematical formality is involved: the approach is informed by what is empirically reasonable rather than by mathematical elegance. Consequently, at the outset three cautionary remarks are made:

(1) Stability is assessed against minor perturbations in the data (ie. data from a new week). This assumes that the same basic message is conveyed by the data week after week. Descriptive accounts show that the same features do recur, but not in every respect. Therefore, in some circumstances we cannot distinguish between instability due to real differences in the data (which ought to produce new classifications) and instability due to the method (which should be minimised). For this reason our approach is approximate.

(2) A more formal approach would help us to measure the amount of mis-classification. Where an artificial data set is contrived, for instance, the true structure is known (it is a parametric form or a set of well-defined geometric shapes) and this provides the base-line against which classifications are assessed. Alternatively, random generation methods are employed, especially Monte Carlo simulation (Lorr 1983, 104-121; see also Openshaw and Gillard 1978). Empirical assessment is far more ad hoc and no general measure of success is available. In the absence of formal measures we inspect the consistency of mean and scaled Cramer values and the membership of bundles.

(3) Computation costs limit the amount of testing that is feasible. Polythetic division is far more efficient than most alternatives (cf. sections 2.5 and 4), but successive deletion of individuals and/or attributes is impractical. Simulations done during program development, however, indicate that polythetic division is less sensitive to outlying individuals than hierarchical methods.

Despite all these reservations an empirical 'first look' is instructive and enables summary results to be presented with added confidence. Furthermore, this investigation is performed in the same spirit as checks on raw data and checks on model estimates.

3.1 Stability of Classification

Polythetic divisions are made from raw data collected during the first few weeks of the survey. Two, three and four bundles are obtained in each case. An indication of the stability of these classifications is revealed by table 3.1. Mean and scaled Cramer values are presented, and (reading across rows) these show similar patterns: mean values increase as K increases, scaled values peak at the 2-bundle solution and decline thereafter. The main point to note comes when columns are read: values within every column are similar and deviations from the average are minor. One week is much like another week. Similar results are seen irrespective of whether 2 bundles or 4 bundles are identified, or in whatever way trips are defined.

Table 3.1

Stability of Cramer Values, Classification with 19 - Attributes

2B = 2 Bundles
3B = 3 Bundles
4B = 4 Bundles

(a) Principal Trips

Weeks	Mean Cramer Values			Scaled Cramer Values		
	2B	3B	4B	2B	3B	4B
1	.31	.34	.35	.22	.20	.17
2	.32	.33	.34	.23	.19	.17
3	.31	.33	.36	.22	.19	.18
4	.33	.34	.35	.24	.20	.18
4-Week Average	.32	.34	.35	.23	.20	.18

(b) All Trips

Weeks	Mean Cramer Values			Scaled Cramer Values		
	2B	3B	4B	2B	3B	4B
1	.26	.27	.30	.18	.16	.15
2	.23	.25	.29	.16	.15	.15
3	.24	.30	.31	.17	.17	.15
3-Week Average	.24	.27	.30	.17	.16	.15

Other features of these replicate classifications are depicted in table 3.2 which is in two parts: (a) for principal trips and (b) for all trips. The first block of results refer to percentages in each bundle. Where there are 2 bundles in week 1, 57% of trips are found in one bundle and 43% in the other, and so on. In general, proportions in one week are very similar to proportions in another week. This is especially true of solutions which produce 2 or 3 bundles (ie. where departures from average conditions are minimal).

Percentages only pick out net similarities across weeks. It may be the case that many trips are allocated differently in successive weeks, and that these shifts are counter-balanced and hidden. In fact, further investigation shows that the net and gross figures do not diverge markedly. Overall, the proportion of trips allocated to bundles remains constant.

One notable departure must be mentioned. Columns in the 4-bundle solution are less similar; in the fourth bundle of week 2 the number of members is particularly small and varies wildly when all trips are considered. Several reasons for this apparent discrepancy are advanced. Most likely a few consumers exhibit peculiar shopping behaviour in week 2; and these individuals have undue influence which leads to the creation of small-member groups. Another reason is that the divisive algorithm can identify up to three well-partitioned groups, thereafter the discriminatory power of classification falls and groups become unstable. Either way our confidence in the 4-bundle solution is reduced.

Major attributes were defined to be those which exceed mean Cramer values by $\pm$ standard deviation. Repeated identification of the same major attributes would suggest that these really are important. Looking at principal trips first, the 2-bundle solution produces almost identical results over each of the 4 weeks: measures of travel (MODE and access to a CAR) are always the major attributes upon which shopping trips are partitioned. All other aspects - what goods are bought, whether the shopper has time for shopping, and so on - are either unimportant or subordinate. In the definition of further bundles, access to a car is consistently influential, so too are attributes for quantities bought and multi-stages.

Turning to consider all trips, the major attribute usually reported is MULTI. Trips are sharply partitioned according to whether they are multi-staged or single-staged. Vehicle and quantity attributes also remain important, and consistently so - just as we saw for principal trips.

A number of interesting fluctuations are seen. In these classifications the location of shops and homes is important (Cramer values are above the mean), and in week one they actually become crucial. While this result is of some geographical interest it is not repeated in subsequent weeks and certainly cannot be regarded as a reliable finding. Another feature is the importance of subsequent activity SACT. The division of all trips must be considered as a collection of influences, which partly depend on activities elsewhere. Principal trips, in contrast, are more purposeful and are delineated by a few major attributes.

Table 3.2 (a)

Stability of Bundle Sizes and Major Attributes:
Classification with 19 - Attributes

(a) Principal Trips

Weeks	Percent of sample in each bundle (ordered)	Major attributes $>\bar{C}+1SD$ (ordered)
2-Bundles		
1	57 43 100	mode car
2	51 49 100	mode sact multi car
3	51 49 100	mode car
4	51 49 100	mode car
Column average	53 48 100	
3-Bundles		
1	43 41 16 100	car items
2	46 33 21 100	multi sact car expend
3	49 33 18 100	mode car marital
4	46 34 20 100	car mode
Column average	46 35 19 100	
4-Bundles		
1	40 24 22 14 100	multi items car
2	45 33 19 3 100	multi sact car
3	33 31 19 17 100	car items mode expend
4	35 28 19 18 100	multi car items
Column average	38 29 20 13 100	

Table 3.2 (b)

Stability of Bundle Sizes and Major Attributes:
Classification with 19 - Attributes

(b) All Trips

Weeks	Percent of sample in each bundle (ordered)					Major attributes $>\bar{C}$+1SD (ordered)
2-Bundles						
1	61	39			100	locat hlocat mode car
2	58	42			100	multi sact items expend
3	58	42			100	multi sact items expend
Column average	59	41			100	
3-Bundles						
1	39	37	23		100	multi mode items
2	54	31	15		100	multi items expend sact
3	53	42	5		100	sact multi pact mode items
Column average	49	37	14		100	
4-Bundles						
1	36	24	22	18	100	multi car
2	46	30	15	9	100	multi items expend sact
3	47	29	14	10	100	multi items expend sact
Column average	43	28	17	12	100	

3.2 Sensitivity to Change

A number of arbitrary changes are made in order to assess the sensitivity of classification. Several attributes are removed: three are qualitatives (MARITAL, EVENING and FROZEN), and one is an ordered multi-state (AGE). The qualitative attribute SEX, denoting the sex of shoppers, is added (currently there is much interest in the division of roles within the family so this attribute might be regarded as informative). All the attributes which are removed or added are minor ones.

Derived is a 16-attribute classification in which the number of disordered multi-states and numerals remains unchanged, qualitatives now number 4 and there are 3 ordered multi-states.

For those attributes common to both models (15 attributes in all) Cramer values are compared in table 3.3. In the 2-bundle solution (table 3.3(a)) the attribute MODE has a Cramer value of 0.64 when 19 attributes are used and 0.68 when 16 attributes are used, and the difference is slight. Differences between important attributes (MODE, CAR, EXPEND and ITEMS) are negligible. The single largest difference is that for DAY; the value declines by 0.14 across the models. Such volatility is significant, but it is exceptional.

The 3-bundle solution (table 3.3(b)) is even less sensitive, and a qualitative description of the three bundles reads just like that presented in section 2.3. DAY is again the most volatile attribute - clearly the effect that day of week has upon activity is bound up with many other factors such as car availablity and the importance of bulk purchasing.

Reported at the base of table 3.3 are mean and scaled Cramer values, these are calculated for the 15 attributes actually presented (not the original models). Virtually identical results are reported. In no case would the arbitrary inclusion or exclusion of marginal attributes affect the main findings.

As a final check the movement of individual patterns between groups is considered. Findings are summarised in table 3.4. Look first at gross changes. The 'no change' situation is described by entries along the diagonal of each table. In the 2-bundle solution 234 individuals are allocated to group 1 and remain there; this number of non-movers represents 93% of all members in the 19-attribute solution and 95% in the 16-attribute solution. Slight changes to the list of attributes do not affect the majority of allocations.

Similarly, 178 individuals remain in group 1 of the 3-bundle solution, irrespective of which classification is applied. This number represents 90% of all members in group 1 whichever solution is studied.

Table 3.3 (a)

Comparison of Models with 19 Attributes and 16 Attributes: Principal Trips

(Classification with 19 attributes is used to arrange the entries)

(a) 2 - Bundles			
Attributes[1]	Cramer Values		Difference
	19 Attributes	16 Attributes	
MODE	.64	.68	.04
CAR	.58	.58	.00
EXPEND	.37	.37	.00
ITEMS	.35	.30	.05
DAY	.34	.20	.14
HLOCAT	.34	.39	.05
SIZE	.33	.29	.04
MULTI	.32	.35	.03
LOCAT	.31	.37	.06
SACT	.28	.33	.05
TIME	.26	.28	.02
DEPFRE	.22	.27	.05
WORK	.19	.20	.01
PACT	.11	.15	.04
GOODS	.07	.05	.02
Mean Cramer[2]	.31	.32	
Scaled Cramer	.22	.23	

(1) Only attributes common to both classifications are listed.

(2) Mean and scaled Cramer values are reported for the attributes actually listed.

Table 3.3 (b)

Comparison of Models with 19 Attributes and 16 Attributes: Principal Trips

(Classification with 19 attributes is used to arrange the entries)

(b) 3 - Bundles			
Attributes[1]	Cramer Values		Difference
	19 Attributes	16 Attributes	
CAR	.61	.65	.04
ITEMS	.56	.52	.04
MODE	.45	.49	.04
LOCAT	.43	.44	.01
EXPEND	.41	.45	.04
HLOCAT	.37	.41	.04
SACT	.37	.36	.01
MULTI	.35	.43	.08
PACT	.31	.27	.04
DEPFRE	.29	.29	.00
SIZE	.29	.24	.05
WORK	.26	.20	.06
DAY	.26	.18	.08
TIME	.20	.22	.02
GOODS	.08	.08	.00
Mean Cramer[2]	.35	.35	
Scaled Cramer	.20	.20	

(1) Only attributes common to both classifications are listed.

(2) Mean and scaled Cramer values are reported for the attributes actually listed.

Table 3.4

Comparison of Models with 19 Attributes and 16 Attributes: Principal Trips

(Numbers in each bundle after reallocation)

2 - Bundles

Gross changes		19 attributes bundles 1	2	total	Net changes
16 attributes	bundles 1	234	18	252	+ 1
	2	12	181	193	- 1
	total	246	199	445	

3 - Bundles

Gross changes		19 attributes bundles 1	2	3	total	Net changes
16 attributes	bundles 1	178	13	1	192	- 8
	2	9	161	11	181	+ 7
	3	13	0	59	72	+ 1
	total	200	174	71	445	

Off-diagonal elements of table 3.4 show the changes which occur. Where there are two bundles, 18 individuals move from group 1 to group 2, and 12 move in the opposite direction. Most sensitive is the third group of the 3-bundle result: the core of non-movers represents only 83% of members, a figure considerably below other groups. As a rule, small-member groups are more sensitive to slight changes, so too are groups defined at a lower level of the divisive hierarchy.

Finally, the total membership of each bundle is quoted. These totals are used to calculate net changes. Changes tend to become larger as the number of bundles is increased. Finer division of the data gives more scope for movement across groups and gives added importance to secondary attributes. Therefore, the whole process of classification becomes steadily more sensitive to minor change.

We conclude that the main features of classification are insensitive to change among minor attributes. This is true whether classification is into 2 or 3 bundles. Small member groups, however, are often poorly defined and may be affected by minor changes.

4 Comparison of Alternative Classifications

4.1 Choice of Technique

Extensive results have been reported for polythetic division. This approach has been checked in a variety of ways. Comparison of results from alternative techniques represents a further stage in the assessment process.

A fear frequently expressed about numerical classification is that substantive results depend too heavily on the choice of technique. Perhaps a different techique would produce contrary results ? This fear arises because different types of data are introduced, initial assumptions vary, and measures of similarity alter. To the extent that different purposes are served, technique dependence is not a serious problem. But where there are arbitrary and hidden biases then fears might be fully justified.

Effective comparison requires a number of common elements - a requirement that is difficult to meet when classifications are designed to serve a variety of purposes. One option has been to use artificial data sets where the underlying structure is known. Mojena (1977) assumed a gamma process to generate a known structure for numeric data. The best techniques were able to replicate the gamma structure. For artificial categorical data Openshaw (1980) ran a number of experiments to compare the performance of agglomerative and divisive techniques. Monothetic, hierarchical and association methods performed badly.

While artificial data help to identify extremely poor techniques, they have not been able to provide a complete ranking of methods. Such a definitive statement is unlikely, anyway, until data measured on a mixture of scales are compared directly. Artificial data raise other problems too: they are liable to be untypical of survey data (which are noisy) and they fail to recognise that techniques are often optimal for certain sizes of problem and not others.

Rather than test techniques on contrived data, which could be misleading, an appraisal that utilises real data is attempted. Several aspects are comparable - qualitatively at least - such as types of attribute, choice of similarity measure and the meaningfulness of partitions. Precisely six aspects are investigated in this survey: purpose, attributes, stopping rules, interpretation, robustness and computation. All these aspects are familiar from previous sections.

Most of the selection criteria point toward techniques that are polythetic and divisive, therefore a qualitative appraisal among this restricted range of techniques seems to be most relevant. Despite general agreement that polythetic divisive strategies are desirable, surprisingly few algorithms exist and here only the iterative partitioning programs are actually applied.

Becoming popular in American biological sciences is TWINSPAN (Hill 1979, Gauch and Whittaker 1981). TWINSPAN is a polythetic divisive algorithm which uses ordination of major attributes to polarise individuals; once polarised, individuals are split into sub-samples. Sub-samples themselves are ordinated and the splitting routine is repeated. There is much to recommend TWINSPAN: no dissimilarity matrix is needed, computation is efficient, and attributes can be measured on different scales.

Also from research in biological science is the work of Ratkowsky (1984). Ratkowsky proposes a number of extensions to the polythetic divisive routines used already, particularly with regard to stopping rules. The approach uses a measure of 'likeness', namely the average similarity of an individual with all members of its group. Rules for effective partitioning and stopping are obtained, but the need to calculate average similarities leads to inefficient programming. Trials using data from the Cardiff consumer panel have proved to be successful for the classification of principal trips. Because of size limitations, however, the technique will never be capable of working with data for all trips.

TWINSPAN and Ratkowsky methods will not be mentioned any further; instead, close examination is made of another approach:

K-means clustering

A set of attributes associated with each person is defined. The aim - using these attributes - is to minimise the distance that separates one pattern from the centroid of each bundle. Once defined it is a simple exercise to allocate individual shoppers among relevant bundles. Each allocation is evaluated and, to improve partitions, a certain amount of reallocation is allowed.

The method is not entirely satisfactory, but to it has accrued a certain amount of popular support. Admirable documentation for K-means clustering is to be found in Hartigan (1975) and Engelman and Hartigan (1981). Transport researchers who are studying the structure, sequencing and scheduling of trips find K-means clustering convenient and informative (Saloman and Ben-Akiva 1982, Koppelman and Pas 1983). An alternative not developed here, yet popular, is based on Ward's method which minimises the variance of distance between attributes for an individual and group centroids (Pas 1982).

4.2 K - Means Clustering

The main features of K-means clustering are examined by working through an example. The aim is to classify individuals according to the mean features of their shopping behaviour over one week. Through this exercise it is possible to comment upon the purpose of classification, attributes, stopping rules, interpretation, robustness and computation.

Example 3 Average Weekly Trip Patterns

(1) Purpose

K-means clustering is a divisive method which starts with all individuals stored in one group. The purpose is to classify details of shopping activity into a salient number of exclusive bundles. Shopping patterns within a bundle are 'close' (in a sense explained later) and patterns in other bundles are 'distant'. The emphasis is on the definition of sharp partitions and no attempt is made to derive meaningful hierarchies.

We can be somewhat more precise. The procedure starts with a pre-specified number of groups K. The initial group is divided into K groups, the means or centroids of which form nuclei for the bundles. Values at these nuclei are compared against attribute scores for every individual in turn and the result is expressed as a 'distance'. Individuals are allocated to the nearest bundle and the mean values for all K bundles are revised. Reallocation of individuals between bundles proceeds in an iterative fashion until the homogeneity of K groups is optimal. In this manner well partitioned groups are obtained. Reallocation destroys the hierarchical structure.

(2) Attributes

Mean values for K groups are compared against attribute scores and the resultant measure is termed distance. By default Euclidean distance is measured; but, where scales vary, standardised distances are defined. It is possible, therefore, to use a numeric attribute such as expenditure (where the range may be several dozen pounds) in conjunction with a disordered list of travel modes (where the range is five discrete states). Less easily handled are qualitative attributes and ordered multi-states. Non-exclusive states are not accepted at all.

The purpose is to classify information about shopping activity into a number of exclusive bundles. Data that describe four attributes are collected for 445 individuals. The number of shopping trips observed over one week is regarded as a primary characteristic; secondary attributes denote the level of expenditure, the mean number of product fields from which goods are bought, and the mean time of purchase. Individuals are allowed to have a few missing entries; in practice this facility is rarely needed.

Geographic influences - such as distance from the activity prior to shopping - are not used in this example although undoubtedly their inclusion would be informative. In fact, the example is highly simplified.

(3) Stopping Rules

An optimum allocation is obtained for a pre-specified number of groups K. Every run will produce K homogeneous groups in which distances are minimised. Specifically, the mean square of distances between attribute-scores and group centroids is minimised. Mean square within a well-partitioned bundle will be (much) less than that between bundles, and the degree to which this is true represents a level of success.

It is quite feasible to run several classification exercises by varying K on successive occasions. After several runs a set of within-group and between-group mean squares are available. An evaluation of absolute within-group values is not very helpful - additional bundles invariably give lower within-group values for each bundle - but an assessment of increments does reveal obvious knick points. Before a knick point, bundles are meaningful (ie. all K groups are informative), afterwards some of the bundles will not be meaningful (ie. some groups are redundant or noisy).

K-means clustering of the Cardiff consumer data shows that the 2-bundle and 5-bundle solutions are the most instructive. Only the former solution is discussed here.

(4) Interpretation

F-ratios are reported, these can be used to describe differences between attributes (rather than to assist in statistical inference). Highest of the F-ratios is that for the number of product fields, this exceeds expenditure and the mean number of trips, and greatly exceeds mean time of purchase.

More informative are the means and variances which describe each bundle. These indicate that K-means clusters and polythetic division do reveal similar results. The two K-means bundles have the following features

(a) Bundle 1

Few trips are recorded. Goods are bought in bulk and expenditure per trip is heavy. There is a distinct mid-day and early afternoon skew. Some trips are undertaken during the early evening.

(b) Bundle 2

Consumer spending is low and purchasing on each of a large number of trips is light. Frequently shopping trips are made over the morning to mid-day period.

Inspection of 'representative patterns' is an alternative way to interpret the results. Those patterns which are nearest to group centroids are selected as representative; this gives a qualitative impression of what each bundle looks like, though a fairer image might be conveyed by the spread of patterns around centroids (Pas 1982). A representative individual in bundle 1 spends £10 on the purchase of goods from about 10 product fields. Three trips, invariably during the early afternoon, are undertaken. In bundle 2 a representative individual spends only £3 on goods from 5 product fields. While average expenditure is low, the frequency of trip-making is high and is concentrated into the morning and mid-day periods.

Bundles differ in relation to the intensity of shopping: one involves a heavy commitment to bulk purchasing, the other is frequent and low valued. A direct comparison of results from several alternative methods of classification is presented in table 4.1. Down one side of the table is a list of attributes; these are selected to be roughly comparable across different methods. In practice, comparability is precluded because the range of attribute-types accepted by a single algorithm is limited.

Lying next to the attributes are representative patterns. The distinction between heavy and light purchasing persists across all methods. As one might expect, the degree of correspondence is greatest when all trips and average conditions are studied.

(5) Robustness

Repetition enables the reliability of results to be tested. For the first week and over four succeeding weeks the K-means clustering algorithm is applied. Various values of K are specified; here the 2-bundle solution is discussed. Table 4.2 shows the week-on-week variation in standardised means for the four attributes. Variation is small and no dramatic departures from the five week average are observed.

A ranking of attributes by F-ratio sizes also proves to be consistent across 5 weeks (except in one instance when expenditure is ranked higher than the number of product fields). Taken together, mean values for each bundle and F-ratios for each attribute imply that the division of the sample into light and heavy buyers is a meaningful one, and is consistently meaningful.

Several problems are mentioned at this point. It is quite common to find that a few consumers are spending much more time and money on an activity than the bulk of people. These outlying individuals unduly influence the definition of bundles. Sensitivity to outliers is uncommon when the number of bundles is small, but for solutions having 5 or more bundles small-member groups can result. Jones et al. (1983) remark that activity bundles , defined from time-budget data, often contain very few members. Similar small-member bundles can arise from the K-means method: over the first month, for instance, merely 35% of individuals are allocated to 60% of clusters in the 5-bundle solution.

Further problems arise from inter-attribute relationships. There is an underlying assumption that attributes are not correlated (ie. they are orthogonal). Inter-attribute correlations are

Table 4.1.

Comparison of Results from Alternative Methods of Classification 2 Bundles Week 1

Method of classification	Attributes	Interpretation	
		Bundle 1	Bundle 2
Polythetic division (a) principal trips	EXPEND ITEMS DAY EVENING TIME	£16 18 items 33% Thursday, 50% Friday to Saturday important one third 10am to noon, 18% after 4pm	£8 11 items 15% Tuesday/ Wednesday, 31% Friday, 26% Saturday daytime half 10am to noon
Polythetic division (b) all trips	EXPEND ITEMS DAY EVENING TIME	£5 7 items 20% Thursday to Saturday majority daytime 75% 10am-4pm	£3 4 items even across the week majority daytime 42% 10am-noon
K-Means	EXPEND ITEMS NUMBER TIME	£10 10 items -many 3 trips 2pm-4pm	£3 5 items - few 6 trips morning to mid-day

Shown are those attributes which are roughly comparable, not all these are significant in every classification.

Table 4.2

K-Means Classification: Standardised Means for Two Bundles and Four Attributes

(Attributes are ordered by decreasing size of mean in bundle 1)

Standardised data	Bundle 1					
	Week					Ave
	1	2	3	4	5	
Mean time of purchase	4.1	3.6	4.1	3.9	3.8	3.9
Mean number of trips	1.5	1.6	1.3	1.3	1.3	1.4
Mean number of product fields	2.9	2.7	3.0	3.4	3.0	3.0
Mean expenditure	1.7	2.1	2.6	2.8	2.7	2.4

Standardised data	Bundle 2					
	Week					Ave
	1	2	3	4	5	
Mean time of purchase	3.4	3.2	3.3	3.3	3.3	3.3
Mean number of trips	2.6	2.7	2.5	2.5	2.5	2.6
Mean number of product fields	1.4	1.3	1.2	1.6	1.3	1.4
Mean expenditure	0.6	0.8	0.8	1.0	0.8	0.8

mostly in the range 0.05 to 0.10, which is low. Correlations between expenditure and product fields, however, reach about 0.4 and are worrying. Transformation of the data prior to classification is sometimes recommended. For instance, preliminary analysis of principal components guarantees orthogonality, but the procedure makes stringent assumptions about the normality of attributes which cannot be upheld where qualitative and ordinal data are used.

(6) Computation

An assessment of efficiency is necessary if the practical worth of classification is to be gauged. There are two aspects to consider: storage of data and passes through the data.

Storage requirements fall dramatically when iterative partitioning is adopted. This was shown for polythetic division and applies again here. An hierarchical routine needs to store a N * N similarity matrix with N(N-1)/2 unique entries. By contrast an iterative partitioning procedure only needs to store the original N * J data matrix. For N=445 shoppers and J=4 attributes the improvement translates into a fall from about 99 thousand entries to almost 2 thousand entries. Partitioning routines, such as K-means clustering, are far more economic.

The number of passes through the data has to be considered too. Indeed, the benefits of economic storage are lost if the whole data matrix has to be read on many occasions. Hierarchical monothetic division, in implementation 1c of CLUSTAN, requires J+3*J*K passes through the data. K-means clustering only makes K passes through the data.

Partitioning routines appear to be far more efficient, but two riders are added. First, hierarchical algorithms can be written more efficiently than those implemented in CLUSTAN 1c (see Openshaw 1980, section 4.3). Second, where partitioning procedures allow final reallocation of individuals the number of passes increases. Therefore, partitioning is normally - but not necessarily - more efficient.

4.3 Discussion

Three main conclusions are to be drawn from the appraisal of techniques.

(1) Complex shopping trips can be classified into a salient number of bundles. The structure of these bundles differs depending on whether principal or all trips are considered.

(a) Principal trips are differentiated by the form of travel to reach shops and by the quantities bought. The sharpest division is made between bulk-buying on car-borne trips, and lighter shopping when travel is by foot.

(b) All trips are more varied and have to be studied in their context. Much depends on the relative location of shops and homes, and on other activities, as well as vehicular movement around the city. The dominant group describes trips that cover short distances on foot and where buying is light.

(2) An initial study of stability shows that similar results are obtained week-by-week, and that this remains true irrespective of whether 2, 3 or 4 bundles are identified or in whatever way trips are defined. These findings confirm how useful it is to perform repeated analyses over several weeks. Also, we note that classification is fairly insensitive to change among minor attributes, but that as the number of groups increases so this conclusion becomes less true.

(3) Comparison against other methods is encouraging. All methods convey a similar message and all methods reveal the same basic partitions. A favourable comparison is drawn against K-means cluster analysis. Polythetic division is adept in the way it handles mixed attributes and in its capacity to process very large amounts of data. The K-means method is efficient but not so flexible.

5 Extensions

5.1 Heuristics

Much research has been led by technology. Some commentators fear that where research is led by technology there is a danger that inappropriate questions are posed, that the user has insufficient control, and that the methods used are insensitive to the richness of human behaviour. Sometimes these fears are over stated, and, anyway, what was true of practices in the past is not always relevant today. The whole process of classification is beginning to show a closer relationship between problem definition, heuristic methods and numerical analysis.

It is possible, for instance, to think about the incorporation of mindful and adaptive features into computer systems. Tentative steps are seen when programs are refined to take account of temporal change and recurrence. More fundamental advances call upon developments in intelligent knowledge-based systems and expert systems, both of which may be applied to the problems of classification.

The notion that both observed behaviour and computational solutions are mindful is tantalising. Since the early writings of Zipf and Greig Smith it has been clear that pattern analysis and classification contain a mixture of properties which arise from actual human behaviour, from the data collected and examined, and from the mind examining it. This is what Williams (1976) meant when he wrote of 'pattern-for-an-agent'. It is now possible to give explicit recognition to these subjective properties, and to turn them to our advantage.

Most of the possibilities are to be found in three areas of research: (a) decision rules, (b) intelligent classification, and (c) cluster definition.

(a) Decision Rules

Decision rules are an essential element of all numerical routines. Typically, the researcher is faced with having to convert a 'feeling' into an explicit rule. Then, the rule can be used to formalise and automate feelings. This is all that classification aims to achieve: an opaque recognition algorithm - 'I feel that shopper A should belong to bundle 1, but I cannot articulate my feeling' - is converted into a transparent recognition algorithm - 'I allocate shopper A to bundle 1 because a set of logical rules tells me to do so'. Only the latter can be automated.

Existing algorithms have very simple rules or grammars; for example, the rule that individuals are allocated to the nearest group centroid. More complex rules could be devised to decide at what level further division becomes meaningless (stopping rules), to take action against outliers, and to assess the validity of partitions.

Another extension comes with the inclusion of 'query-the-user' facilities. Through question-and-answer sessions classification could be used to explore ways of arranging salient information and to assess the sensitivity of partitions in the face of abnormal individuals or minor attributes.Where the session is interactive or interrogative a record can be kept and used to update rules. This leads to the second area of research, namely intelligent classification.

(b) Intelligent Classification

The simplest case is that of adaptation by example: from an initial solution knowledge is obtained which helps the algorithm to converge more efficiently when more data are supplied. When classification of a sub-sample, for instance, provides an initial allocation (which is used later in a large problem) a form of low-level adaptation is happening. A fuller version of adaptation occurs when classification for one week is automatically carried forward, starting values being updated as information from more recent weeks becomes available.

As the degree of formality increases, so greater attention is given to rule learning. Adaptation uses past solutions to update current allocations, but it is not a mindful process. No creative or intelligent aspects are involved. By contrast, rule learning is mindful and builds inductive rules from logical and linguistic clauses.

A clause might be of the form: ' to allocate person A, and A has young children, then shopping en route from school must be considered as a feasible option'. Evaluation of such a clause could highlight a factual fault (the clause is incorrect), or indicate that there is a control fault (the clause is true but it would be an undesirable rule), or show that the rule is satisfactory. The example here is imprecise and probably it is a control fault, in which case the clause should be modified. Discussion of these issues is to be found in Quinlan (1979) and Bundy et al. (1985).

As an aid to classification the construction of rules ought to generate more reliable results at lower cost. Knowledge of infeasible partitions could be used to close-off certain routes in the iterative process. The task of searching for a numerical solution would become easier, and large economies would be gained.

If rules show that shopping during the morning is not an option for those who work then the algorithm need only consider the allocation of persons to bundles where morning events are excluded. The parallel here with constraints in space-time studies is direct. At present space-time studies conceive of coupling and capability constraints but find it difficult to apply these concepts. With a learning program it is possible to obtain constraints from inductive logic and then use these constraints to solve future problems.

(c) Cluster Definition

Algorithms written recently allow individuals to be reallocated between final bundles. This facility is available for all the major techniques discussed in sections 2 and 4. While reallocation destroys the hierarchy and tends to increase the cost of computation, it serves to emphasise how group membership is not always clear cut. Indeed, it is likely that some members of bundle 1 only just miss being in bundle 2.

There are many occasions when patterns of activity grade into one another and where the imposition of abrupt boundaries is misleading. Zadeh (1977, 251) refers to the existence of vague boundaries: 'Thus, given an object X and a class F, the real question in most cases is not whether X is or is not a member of F, but the degree to which X belongs to F'. It is stated that on the margins of each bundle there are grey areas, or fuzzy boundaries, in which it is uncertain whether an individual should be allocated to one bundle or another. Such fuzziness can be expressed as a band of error, declining in its intensity away from the boundary itself.

The degree to which fuzzy boundaries are associated with mis-classification depends upon the resolution of analysis. A 2-bundle solution, for instance, has a lower boundary length per total area than a 5-bundle solution, and therefore the chance of mis-classification is less in the former. This tendency for mis-classification to rise with resolution is confirmed when results from reallocation in the divisive algorithm (RECAN) are recalled and when the amount of movement between 19-attribute and 16-attribute models is re-assessed (section 3.2). The problem of resolution in classification is a well-documented research topic in remote sensing, regionalisation and computer cartography.

Research into fuzzy boundaries will continue (see Ruspini 1970 and Chrisman 1981). It may even become possible to express our confidence in the allocation of members to bundles using some notion of error bands. However, the original purposes of classification should not be forgotten: the aim is to summarise data, to do so efficiently and in a manner that helps communication. By concentrating on marginal members, the concept of fuzzy boundaries may obscure the really important and really meaningful differences between the majority of individuals. A degree of caution is necessary.

5.2 Applications

Just three extensions have been noted: decision rules, intelligent classification and cluster definition. Unfortunately the literature tends to be obscure, pre-occupied with syntax and notation, and largely non-operational (at least for large N). The basic ideas, however, remain tantalising and algorithms for fuzzy clustering are starting to appear.

Already, exploratory work is beginning in the analysis of personal movement, choice and activity. Dynamic discrete choice modelling is attempted by Hirsh et al. (1984). These authors view decision-making as a series of evaluations: alternatives are evaluated in one time period and a decision is made; during the next time period more alternatives are evaluated in the knowledge of earlier decisions and with additional information about the choice environment. This procedure is used to investigate several policy issues, including the impact of new shop opening hours and flexible working hours.

The affinity with adaptive algorithms is explicit in the work of Hirsh, Prashker and Ben-Akiva, similarly in the heuristic models proposed by Root and Recker (1983). These latter authors propose a dynamic programming framework. During a pre-travel phase an individual decides what patterns of behaviour are feasible, and these are collected together as a programme of planned activities. Travel, when it finally occurs, can upset earlier plans (because of unforeseen congestion or unforeseen intervening opportunities) so the programme of planned activities is modified. The process of modifying and updating plans gives rise to a dynamic programming framework, where future plans are influenced by random disturbances, by past activity and by the travel budget that remains. Dynamic activity programming has yet to enter the operational phase.

Most pragmatic of recent work, and the closest in spirit to traditional classification, is CARLA (Jones et al. 1983). Using the terminology of rule learning, at least three conditions are identified:

(i) Transparent rules

For example, the logical rules that say 'I cannot be in two places at once' and that 'I cannot leave before arrival' are easily written into an algorithm.

(ii) Potentially transparent rules

During an interview, or game, the participant informs the algorithm that 'car owners have a preference for shopping at freezer centres'. Some such rules may be imprecise, others may be modified and incorporated within an algorithm as transparent rules.

(iii) Opaque rules

Most shoppers follow an habitual, daily routine which is unarticulated and often hidden from researchers. A rule learning algorithm, however, might discover regular scheduling and coupling rules by means of logical induction.

Jones et al. (1983) do not use rules in quite the same way, but the links with rule learning and intelligent classification are clear enough. CARLA itself is a mathematical algorithm that attempts to operationalise several heuristic rules; it does not learn or construct rules. Search time is reduced because infeasible patterns are dismissed. Empirical changes to activity patterns are simulated in response to revised opening hours, the construction of new superstores and the purchase of family cars.

A problem that has not been breached by activity studies thus far is the status of 'behaviour'. Most studies imply that real behaviour occurs in a mindful way and that the decision to shop is in some sense replicated within the algorithm. These are matters which belong to the realms of cognitive psychology and, significantly, many software engineers are turning to personal construct theory and perceptual theories.

Classification, however, is such a mechanistic exercise that behavioural connotations are probably misplaced and may even prove to be unhelpful. To reiterate, classification algorithms may become more mindful and knowledgable, but they remain tools for data analysis - nothing more and nothing less.

CHAPTER 4

PROBABILITY AND CONSUMER ACTIVITY

An angel's intervention would suffice to change everything, so it isn't surprising that one thing cannot be proved to be the cause of another thing. Even if one must always try, as I am doing.

Umberto Eco (1984)
'The Name of the Rose'

1 Introduction

Many empirical results were presented in part I of the thesis. In the discussion of these results it was suggested that some factors influence consumer behaviour far more than others. An examination of raw figures, however, showed how difficult it was to isolate truly significant factors from those having the 'potential' to influence behaviour. Nor was it possible to be confident in talking about associations between factors. By contrast, a modelling framework allows us to be more definite and precise.

Some very simple descriptive models are developed in this chapter. These models enable us to explore several substantive issues, such as the decision to combine family maintenance activities with shopping, the decision to shop early in the evening, and other questions to do with the scheduling of trips for the purchase of goods. Apart from their substantive contribution, these models serve as a prelude to the integrated approach of chapter 5.

Stochastic process theory is used to define a number of basic distributions which characterise the data. These distributions are seen as benchmarks, providing theoretical norms against which observed values may be compared. Often the basic distribution is a 'good enough' description and all variation in the data can be ascribed to random components. However, a family of regression-type models is needed if geographical, transport and marketing variables are to be incorporated within the modelling framework.

1.1 Distributions for Count Data

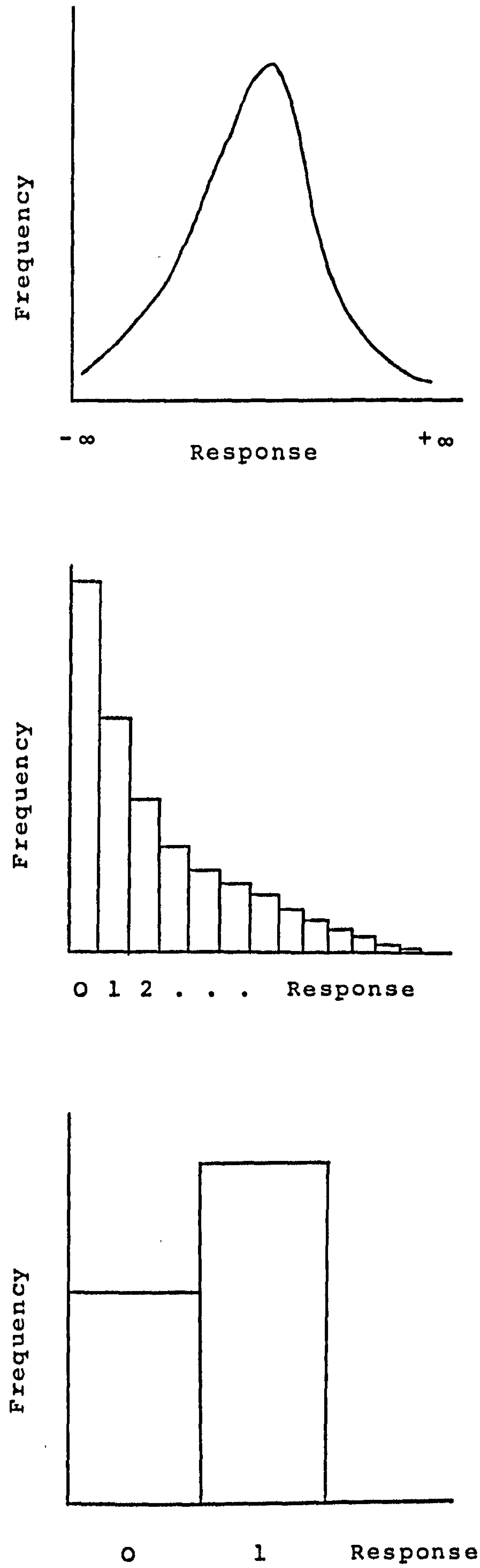
Many aspects of human behaviour are conceptualised as if they are recurrent, repetitive and independent events: the occurrence of trips to a city centre store, the number of shopping events within one week, and so forth. Conventionally data for a series of events are described by the poisson process.

The poisson process generates a discrete distribution of non-negative integers. These integers are independent events which occur in time and space. Predictions from a poisson process are helpful benchmarks against which more regular outcomes can be compared. It may be objected that the poisson process is unrealistic, indeed it is. Human actions are purposeful, planned and evaluative. Yet often the observed response looks haphazard and under such circumstances it is reasonable to suggest that behaviour appears to be random (even when we know that behaviour is shaped by minds that do not act randomly). When we say that the poisson process describes human behaviour this is what we mean.

The characteristic shape of the poisson distribution is depicted in figure 1.1 (b). Zero entries are numerous (ie. many consumers do not record any events). The mean value is low and the average rate of incidence is about 0.5 to 1.5 events per consumer. The long tail after the mean shows how a few

Figure 1.1

Distributions for Different Types of Response Data



(a) Continuous Data

normal
regression

(b) Count Data

poisson
regression

(c) Choice Data

logit
regression

consumers record much higher rates of incidence.

Formally, if each consumer is assumed to have an equal and independent chance of recording an event, then the probability of r events is:

$$p_r = e^{-m}m^r/\Gamma(r+1) \qquad \text{for } r = 0,1,...$$

where e is the exponential function, m is the mean number of events, and $\Gamma(.)$ is the gamma function.

Only one estimate is required, the value of the mean m, and this is calculated directly from raw data. Theoretical values are obtained when the poisson distribution is fitted to a series of r events. The degree of fit between empirical and theoretical distributions is assessed from χ^2 statistics or from informal 'eyeballing'.

By definition, the poisson mean equals the variance, In the whole sample, however, there may be extra variation. Some consumers, for instance, have better access or are more mobile; for whatever reason these people will reveal a higher long run rate of incidence than other people. In effect, there is a collection of poisson distributions whose mean rates (collectively) describe another 'shape' such as the gamma distribution. In this manner the compound poisson or negative binomial distribution is defined.

The negative binomial distribution is used to represent a two-dimensional stochastic process which arises from two standard assumptions. In the case of consumer purchasing behaviour these assumptions are:

(1) Purchases at a particular shop, by a single consumer in successive equal time-periods, are independent and follow a poisson distribution with a constant mean m. The mean can be regarded as an individual's average rate of purchasing in the long run.

(2) The long run average rate of purchasing at a particular store varies from consumer to consumer, and follows a gamma distribution in the whole sample.

Given the mean rate of incidence m and the negative binomial exponent (or 'shape' parameter), k, the probability of r events is:

$$p_r = \frac{\Gamma(k+r)}{\Gamma(r+1)\Gamma(k)}\left(\frac{m+k}{k}\right)^{-k}\left(\frac{m}{m+k}\right)^{r} \qquad \text{for } r = 0,1,...$$

Three methods are available to calculate the negative binomial exponent:

(1) The method of moments, which is based on the observed mean and observed variance.

(2) By the method of mean and zeros, where the number of

zeros is defined as the proportion of consumers who do not record any events.

(3) Through the method of maximum likelihood.

Maximum likelihood estimates are the most efficient, but these are cumbersome to derive. Least efficient is the method of moments. For hand calculations the method of mean and zeros is efficient and direct.

Example <u>Trips to a Suburban Superstore</u>

The aim is to find a theoretical distribution that describes data about the number of grocery trips to a suburban superstore. A sample of 410 potential customers is drawn from the catchment area of the superstore. Rates of trip-making are recorded over a 4-week period, for instance 205 consumers do not make a trip, while 1 shopper makes 6 trips (table 1.1, column 2).

The average number of trips is 0.77 and the observed variance is 0.97. Once we know the mean, theoretical poisson estimates are easily obtained. For r = 1:

$$p_r = e^{-m}m^r/\Gamma(r+1)$$

$$= e^{-0.77}0.77^1/\Gamma(1+1)$$

$$= 0.357$$

To find the actual number of individuals, poisson estimates are multiplied by the sample size (ie. p_1=0.357*410=146).

Theoretical results for the poisson model are shown under the column headed T_1 in table 1.1. The fit is not perfect but it is good. The number of consumers with a trip-rate of zero is under-predicted, and the number of consumers who undertake one trip is over-predicted.

Perhaps there is areal variation in the purchasing power, or mobility, of consumers. These influences give rise to different mean rates of trip-making and we shall assume that these rates follow a gamma distribution. The resultant compound poisson model requires two estimates to be derived: values for the mean and the negative binomial exponent, k.

To calculate the exponent k the simplest method is from moments:

$$k = [m_1(m_1/m_2)] / [1 - (m_1/m_2)]$$

For example, where m_1=0.77 (mean) and m_2=0.97 (variance) then k has a value of 2.97.

Table 1.1

Trips to a Suburban Superstore:
Poisson and Negative Binomial Models

Number of trips per shopper	Observed number of shoppers	Theoretical number of shoppers: Poisson	Negative binomial calculated using method of: moments	mean & zeros	Discrepancy		
	O	T_1	T_2	T_3	T_1-O	T_2-O	T_3-O
0	205	190	207	205	-15	2	0
1	130	146	126	128	16	-4	-2
2	55	56	52	52	1	-3	-3
3	11	14	18	17	3	7	6
4	5	3	5	5	-2	0	0
5	3	1	2	1	-2	-1	-2
6	1	0	0	0	-1	-1	-1

Sample size	410
Proportion of non-shoppers	0.5
Proportion of shoppers	0.5
Average number of trips per shopper	0.77
Variance of trips per shopper	0.97
Poisson parameter	0.77
Negative binomial exponent (moments	2.97
(mean & zeros	3.29

Alternatively, the mean and proportion of non-trip-makers (p_o=0.5) can be used to find the exponent k. First a value c is calculated from:

$$c = -m_1/\ln p_o$$

Then the value c is checked in tables to find the exponent k (Chatfield 1969). In this case k = 3.29.

Values for r events are calculated by placing m=0.77 and k=3.29 (or k=2.97) into the negative binomial expression:

$$p_r = \frac{\Gamma(k+r)}{\Gamma(r+1)\Gamma(k)} \left(\frac{m+k}{k}\right)^{-k} \left(\frac{m}{m+k}\right)^{r}$$

The proportion of consumers making one trip is:

$$p_r = \frac{\Gamma(3.29+1)}{\Gamma(1+1)\Gamma(3.29)} \left(\frac{0.77+3.29}{3.29}\right)^{-3.29} \left(\frac{0.77}{0.77+3.29}\right)^{1}$$

$$= 0.312$$

Multiplying p_1 by the sample size gives a theoretical number of 128 visitors to the superstore.

Two theoretical negative binomial distributions are shown under the columns headed T_2 and T_3 in table 1.1. The fit is good and both distributions are improvements over the poisson estimates. Moreover, the method of mean and zeros provides more accurate estimates of trip numbers. Both methods slightly under-estimate the number of very frequent trip-makers; this is common when mean rates and variances are low.

Neither the poisson nor the negative binomial distribution is new to statistics and spatial science. These distributions were originally applied in studies of proneness to, and recurrence of, accidents and illness (Greenwood and Yule 1920). During the 1960s a large volume of research into quadrat counts and point pattern analysis arose in geographical and ecological sciences (reviewed by Haggett et al. 1977, 414-36). An early example that brought these studies into a spatial-retail context is afforded by Rogers (1965). Rogers modelled clusters of different kinds of store in Stockholm; the location of shops in city quadrats was essentially poisson, but the uneven spread of purchasing power gave a gamma distribution in the whole sample of shops.

The first published example in the literature of consumer behaviour was a study of purchasing rates over 26-weeks by 2000 households (Ehrenberg 1959). Many applications have been made in the intervening years, especially for the analysis of branded goods (Ehrenberg 1972,1975, Chatfield et al. 1966). Only recently have these models been applied to the geographical aspects of consumer behaviour, such as recurrent shop choice, rates of purchasing at shopping centres, and the incidence of trips (Wrigley 1980, Frisbie 1980, Dunn et al. 1983, Kau and Ehrenberg 1984, Wrigley and Dunn 1984b).

1.2 Distributions for Choice Data

Conventionally consumers are believed to make decisions along a continuum of possibilities. In micro-economics a person is seen as demanding more or less of a good depending on price variation and total expenditure. Choice is expressed as a continuously differentiable demand function. As a result, the calculus of marginal analysis is available for the study of demand and supply,and for the analysis of public welfare and household production.

Many decisions, however, are made from small sets of lumpy or discrete alternatives. The number of exclusive options is limited and choice is said to occur at the extensive margin. The central question is not whether a consumer will demand more of Sainsbury's, but to find the qualitative threshold between going to Sainsbury's or going to Tesco (see figure 1.1 (c)).

Choice between discrete alternatives may be expressed in terms of probability theory. For the purpose of illustration, assume that something varies across a sample of consumers and that this variability is described by a series of component scores. Scores are transformed into standard normal deviates to give index values, denoted z_i. The probability p that individual i will choose an alternative, given the value of z_i, is:

$$p_i = f(z_i)$$

where f(.) denotes a cumulative probability function. Only cumulative probability distributions which lie within the unit interval [0,1] are of interest. There are two main candidates: the cumulative logistic probability function (which gives rise to logit models) and the cumulative normal probability function (which gives rise to probit models).

(a) Logit Models

Choice probabilities are derived from the logistic curve:

$$p_i = 1 / (1 + e^{-z_i}) = e^{z_i}/1+e^{z_i}$$

where e is the exponential function.

A related expression is given by the log-odds of choice:

$$\ln[p_i/(1-p_i)] = z_i$$

where ln is the natural logarithm to the base e.

These logistic/logit expressions give probabilities that lie within the unit interval and which describe the familiar S shaped cumulative growth curve. Consumers whose choice probabilities are at the middle of the curve are indifferent between alternatives and are most responsive to changes in z_i. Whereas consumers committed to one or other alternative are unlikely to alter their behaviour without substantial changes to z_i.

(b) Probit Models

Again, assume that there is a series of index values z_i. The probability of a choice is calculated from the cumulative normal probability function:

$$p_i = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z_i} e^{-s^2/2} d_s$$

where s is a random variable which is normally distributed with zero mean and unit variance.

It should be noted that estimation of probit models involves numerical integration and the specification of more parameters than is true for logit models. Extension to the case of multiple-choices increases the computational effort, to the relative disadvantage of probit models.

<u>Example</u> <u>Choice of Shopping Precinct</u>

Assume that a sample of 410 consumers have the choice of patronising a new shopping precinct or of going elsewhere. We wish to find the probability that consumer i will patronise the new precinct. Let the individual's decision depend upon a general appraisal of utility, such that high utility is associated with a high probability of patronage. Levels of utility may depend on the quality of service or the range of goods that can be bought; the precise explanation is not important. Levels of utility are measured in 'utiles'. Across the sample utiles range from 102 to -102, and are normally distributed.

The utile associated with consumer i is transformed into a standard normal deviate z_i:

$$z_i = (u_i - \bar{u})/s$$

where $\bar{u}$ is the (zero) mean and s is the sample standard deviation of 33.3 utiles. For a consumer whose shopping at the precinct is worth 102 utiles the index z_i has a value of 3, and so forth. Response probabilities are obtained from a transformation of utilities which vary along the whole real line, this is achieved using the cumulative logistic probability function:

$$p_i = 1/(1+e^{-z_i})$$

For the consumer who records 102 utiles the response probability is:

$$p_i = 1/(1+e^{-3}) = 0.95$$

So, there is a 95% chance that a consumer who expects to gain much utlity from shopping at the new precinct will actually go there.

Some utility values and response probabilities for the logit model are reported in table 1.2 (columns 1 to 3). Notice how the response alters: between z_i values of -0.5 and 0.5 the probability changes by 0.24 percentage points, whereas from -1.5 to -3.0 the change is only 0.13. Probabilities are unresponsive when utility is extremely low (consumers are adverse to the precinct and remain adverse), or very high (consumers are strongly committed to the precinct), and only show marked differences in the middle of the range.

Probabilities for the probit model are obtained in a similar manner, though calculations are cumbersome. A few results are presented in column 4 of table 1.2. Interpretations are virtually the same as those reported for logit models, except that the responsive/unresponsive sections of the probability function are more sharply defined. In general, the logit model is a good approximation for the probit model.

Clear introductions to these topics are found in Pindyck and Rubinfeld (1981), and Domencich and McFadden (1975). An account of the relationship between discrete choice analysis and marginal micro-economics is contained in Deaton and Muellbauer (1980).

Table 1.2

The Decision to Patronise a New Shopping Precinct: Logit and Probit Models

Raw utility (utiles) u_i	Adjusted utility (z-scores) z_i	Cumulative logistic probabilities (logit)	Cumulative normal probabilities (probit)
-102	-3	.05	.001
-68	-2	.12	.02
-51	-1.5	.18	.07
-34	-1	.27	.16
-17	-0.5	.38	.31
0	0	.50	.50
17	0.5	.62	.69
34	1	.73	.84
51	1.5	.82	.93
68	2	.88	.98
102	3	.95	.999

A similar example is to be found in Pindyck and Rubinfeld 1981, 288.

1.3 Regression-Type Models

Having sketched the basic features of incidence and choice models it is theoretically straightforward to incorporate geographical, planning and marketing influences. The general case involves the definition of observed variables and an assumption about the error distribution.

The standard linear model is defined as:

$$y_i = \mu_i + \varepsilon_i$$

where y_i is the observed response by consumer i, μ_i is the expected value of the response and ε_i is a randomly distributed error term.

In standard linear regression the error term is assumed to be normally distributed and there is a direct link between μ_i and the linear combination of terms $\underset{\sim}{x}_i'\underset{\sim}{\beta}$:

$$\mu_i = \underset{\sim}{x}_i'\underset{\sim}{\beta}$$

Terms on the right hand side are called linear predictors and comprise the vector of observed independent variables x and the vector of corresponding parameter estimates $\underset{\sim}{\beta}$ (including the constant term).

In general, expected values of the response variable are not directly linked to linear predictors and some form of transformation becomes necessary:

$$\text{link function } (\mu_i) = \underset{\sim}{x}_i'\underset{\sim}{\beta}$$

The link in a normal regression model is the identity function. Given this general form it is possible to regard poisson and logit regression models as special cases, each with distinctive error terms and link functions.

All these models are estimated by the method of maximum likelihood. A package, such as GLIM, enables estimates for the simplest models to be calculated (Baker and Nelder 1978, O'Brien 1982), otherwise numerical estimates can be obtained with the aid of subroutine libraries (for example, NAG 1983).

(a) Poisson Regression

Variables that are believed to influence incidence are incorporated within a linear predictor of the standard form. Error terms describe a poisson distribution. The link between linear predictors and the mean number of events is a logarithmic transformation of the form:

$$\ln(m_i) = \underset{\sim}{x}_i'\underset{\sim}{\beta}$$

or

$$m_i = e^{\underset{\sim}{x}_i'\underset{\sim}{\beta}}$$

where $m_i=\mu_i$. Strictly, means from the poisson model should be expressed as predicted values $\hat{m}_i$ but for simplicity the '^' notation is not used. Therefore, the probability of r events is given by a standard poisson model that is augmented by linear predictors:

$$p_{ri} = e^{-e^{(\underset{\sim}{x}_i'\underset{\sim}{\beta})}} e^{(\underset{\sim}{x}_i'\underset{\sim}{\beta})^r} / \Gamma(r+1)$$

Estimation is by the method of maximum likelihood and use is made of an iterative re-weighting procedure. Few applications of poisson regression have been reported in the geographical literature. One exception is the re-evaluation of spatial interaction models undertaken by Flowerdew and Aitkin (1982). These authors argue that the movement of people, vehicles and goods from one place to another generates count data and that gravity models which assume interaction data to be continuous are mis-specified.

(b) Logit Regression

The incorporation of observed variables into logit models follows the same line of reasoning as that presented for poisson models. The error distribution and link function need to be specified: the error is binomial and the link is logit.

The odds of consumer i choosing one alternative p_i over another $1-p_i$ is a log function of linear predictors:

$$\ln[p_i/(1-p_i)] = \underset{\sim}{x}_i'\underset{\sim}{\beta}$$

or

$$p_i = 1/(1+e^{-\underset{\sim}{x}_i'\underset{\sim}{\beta}})$$

Strictly, responses from the logit model should be expressed as predicted probabilities $\hat{p}_i$ but for simplicity the '^' notation is not used. The index value of the logit expression is calculated from the sum of parameter estimates for all relevant independent variables:

$$\ln[p_i/(1-p_i)] = z_i = \underset{\sim}{x}_i'\underset{\sim}{\beta}$$

Over the past decade logit models have been applied to a wide range of problems in transport and economic sciences (Domencich and McFadden 1975, Hensher and Johnson 1981). More recently, applications have been made in spatial and environmental research (Wrigley 1985).

A study was made of how a sample of residents living in Pittsburgh reached their shopping destinations. Domencich and McFadden (1975) used this information about travel choice to illustrate a simple logit model. The aim was to predict the choice of travel by car as against public transit. For instance, as walking time to a public transit stop increases, so the likelihood of travelling by car increases.

2 Incidence and Choice Models

Consumers make numerous decisions; they have to decide which shop to patronise, how to get there, how much to spend and what amount of time can be allocated. Many of these decisions are linked together through a schedule of activities, where activities are viewed as a series of chained events which follow a spatial and temporal sequence.

Schedules may be complex and may generate rich patterns of movement. Indeed, for many consumers the oft expressed interaction between retail potential and home location soon becomes unrealistic. The working shopper who buys goods during the lunch-hour or on the journey home, for instance, defines access in terms of nearness to workplace or proximity to transfer points on the public transport network, rather than nearness to home.

Some of the models introduced in the previous section are used to illustrate several aspects of activity scheduling. Looked at first is a poisson regression model; this is designed to help us predict the incidence of trips which combine family maintenance activities with shopping. A second model, based on logit regression, gives us an understanding of the influences that lie behind a consumer's decision to participate in early evening shopping. Finally, brief consideration is given to how one might model the daily incidence of grocery shopping.

2.1 Incidence Models

Commonly, aspects of human activity and movement are recorded as counts:thus, a record is kept of how many trips are described by a home-shop-home pattern or the frequency of car-borne journeys each week. One person might make 2 journeys by car within a week, another person might make 5 such journeys, and across the whole sample we can think of a counting process.

Count data are required by store managers who wish to monitor levels of demand and penetration, and by urban planners who need to determine peak flows around shopping centres and pedestrian movements between stores.

2.1.1 Poisson Regression

Example 1 Family Maintenance Activities and Shopping

To illustrate the poisson counting process consider the number of grocery shopping trips which are made in conjunction with other family maintenance activities. Invariably visits to shopping parades serve a dual purpose; goods are bought and other family maintenance tasks are performed. These varied tasks include everything from the collection of children who attend primary school, to financial affairs at High Street banks, building societies, estate agents and insurance offices.

The close ties between shopping and family maintenance have been stressed by several geographers, especially in the context of novel forms of retailing and the changing location of service outlets (Tivers 1982, Clarke 1984, Clarke and Macgill 1984). Analytically, linkages between several activities may be incorporated into trip-chaining models (Burnett and Hanson 1979, Adler and Ben-Akiva 1979).

The response variable is defined to be the number of occasions when grocery shopping is preceded or succeeded by other family maintenance activities. Observed responses y_i, for individuals $i = 1,2,\dots,N$ are regarded as realisations from a poisson process with mean m_i (these are predicted values). These means are derived from the parameter estimates $\beta_0, \beta_1, \dots, \beta_K$ associated with a constant and K observed variables.

The observed distribution of responses is shown in figure 2.1. Some 45% of counts are zero entries. The mean is low and trailing away to the right is a long tail. Amongst the positive counts, 31% of households record between 1 and 4 trips. Thereafter the number of counts declines steadily, so that merely 3% of households record more than 20 trips of the 'shopping-maintenance' type. Closer inspection of responses points to the influence of timing: incidence is concentrated into weekdays before 10 am and between 2 pm and 4 pm. Furthermore, family maintenance activity is more likely to precede a shop visit than succeed it. Often the return flow is homeward.

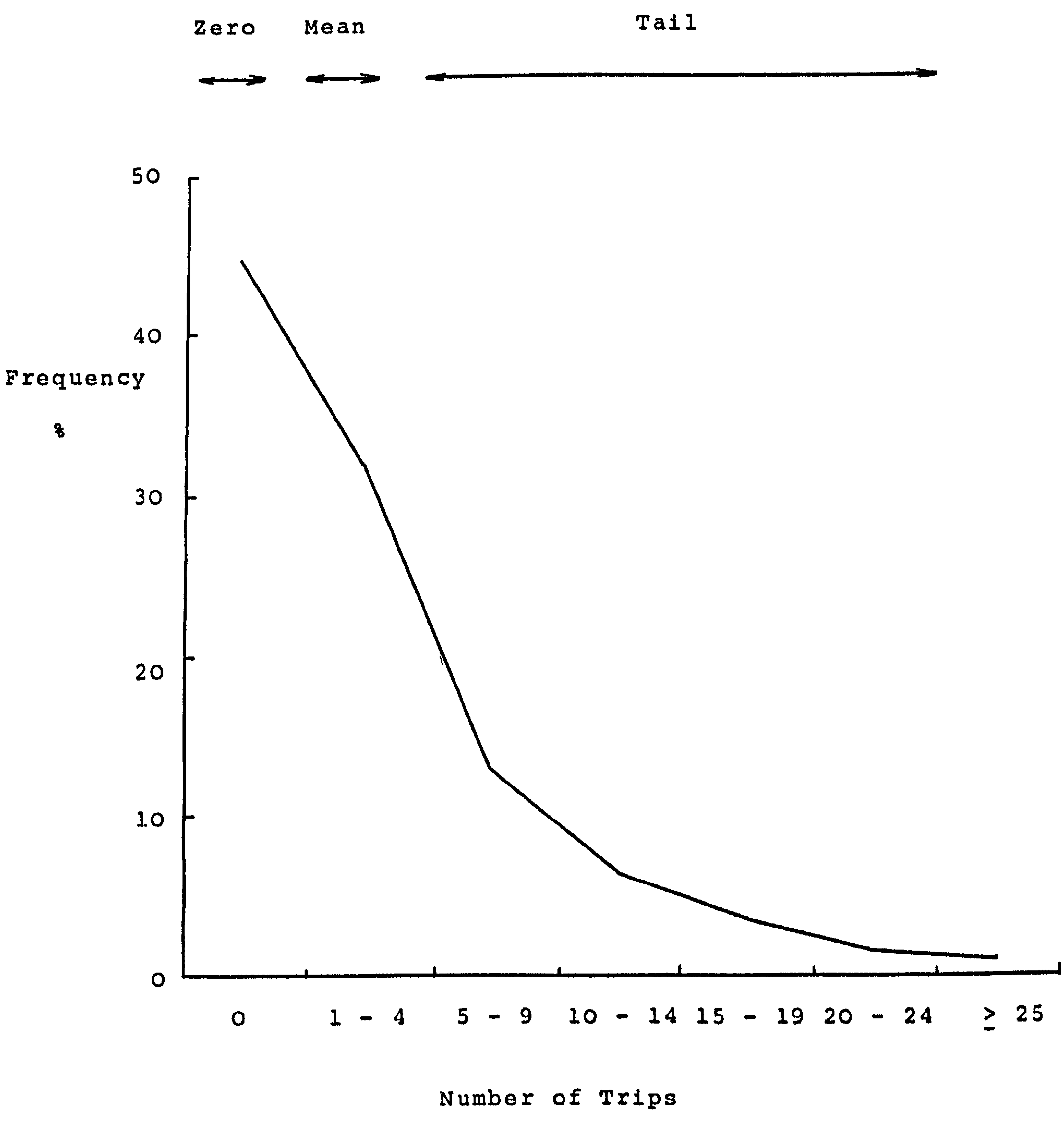
The incidence of multi-purpose trips is likely to be influenced by many observables, as well as unobserved random predilection. Using the knowledge of travel behaviour that we acquired from descriptive studies three variables are defined here: (a) the number of children in the household; (b) a binary indicator of whether the shopper works (part-time or full-time) or not; and (c) the level of household income. Acronymns are CHILD, WORK and INCO respectively. Persons who refused to state their income were removed from the model, this does not seriously bias results but the sample falls in size to 304 individuals.

These variables summarise information about the opportunity to link grocery shopping with family maintenance, and the means of taking full advantage of opportunities.

Family tasks rise with the addition of more children - schools are visited, more clothes are purchased, food and convenience goods are bought in bulk - therefore patterns of movement become locked into a complex schedule of related activities. About 50 families have three or more children, and among these we expect incidence to be high.

Figure 2.1

The Poisson Distribution of Grocery Shopping and Family Maintenance Trips



The busy working consumer seeks to minimise family maintenance tasks. Possibly the chauffeuring of children, attendance at clinics, and dealings with family advisers are minimised, and most groceries are bought weekly at a superstore. Besides a reduction in the absolute frequency of shop visits, some shopping may be done en route to and from work, rather than in combination with other activities.

Household income, the third variable, operates at two levels. High income is likely to have a positive influence on the total number of trips undertaken (irrespective of purpose); this is because the shopper's capacity to make trips is widened (bearing in mind travel costs, entrance fees, and purchases at the destination). Income is of interest as a measure of effective purchasing power. It should be noted that gross income is reported whereas disposable income is more relevant.

A model that includes the variables is fitted and the following estimates are derived:

$$\ln[\text{mean}(m_i)] = -0.31 + 0.21\ \text{CHILD}_i - 0.47\ \text{WORK}_i + 0.27\ \text{INCO}_i$$

$$(2.4)\quad (8.9)\qquad (6.6)\qquad (11.9)$$

$$\text{df} = 300 \quad \text{deviance } D = 1771 \quad \text{chi-square } \chi^2 = 2364$$

where asymptotic values of the t-statistic are in parentheses. 'Deviance' in these results is a value returned by the GLIM statistical package, and it expresses the likelihood associated with the current model.

All signs accord with expectations: given a rise in the number of children and rising income there is a corresponding increase in shopping trips chained with family maintenance activities. Conversely, as the amount of time devoted to paid employment expands so the incidence of these chained trips falls. On a two-tailed test all three parameter estimates are significant at the 95% level.

Of the variables not entered into the final model car availability probably is the most important, and in larger models it has a significant positive effect at the 95% level. Certainly car travel can assist trip-chaining in some circumstances, but where parking restrictions and traffic congestion are heavy it may be impossible to stop frequently. Moreover, many of those who perform family tasks either do not have access to a car or they travel short distances.

A few interpretations of the poisson model are presented in table 2.1. Six household types are defined from values of three socio-demographic variables. The mean predicted number of trips is given in the final column. Thus, a household with income in the range £2-3,000 which is without children and where the shopper does not work (type 1), is predicted to undertake 1.6 trips which link grocery shopping with family maintenance.

Table 2.1

A Poisson Model of Family Maintenance Activity: Six Household Types

Household type	Children (number)	Work status (yes/no)	Income (groups)	Predicted mean number of trips
1	0	0	3	1.6
2	1	1	5	2.2
3	3	0	5	5.3
4	3	0	7	9.1
5	2	0	4	3.3
6	5	1	6	6.6

Global goodness of fit measures are roughly analogous to those of conventional regression. A likelihood ratio ρ^2 is defined as:

$$\rho^2 = 1 - \frac{\text{likelihood of estimated model}}{\text{likelihood of null model}} = 1 - \frac{L_{max}}{L_O}$$

Likelihood of the null model L_O is evaluated for all parameters set to zero, except the constant. At the other extreme, the model fitted with parameters will converge upon a maximum likelihood estimate at L_{max}. We note that deviance is greatest in the null model and least in the estimated model, and that therefore minimisation of deviance is formally related to the maximisation of likelihood.

For non-normal regression models further details are outlined by Pindyck and Rubinfeld (1981, 311-12) and Nelder and Wedderburn (1972).

The calculated value of ρ^2 is 0.13. Similar values are reported in the literature for non-normal regression models, yet these values still look low. Before passing judgement, however, we need to establish what constitutes a good fit and for this reason attention cannot be confined to global measures alone. If the variables are relevant to the problem at hand it may be of more importance to assess the discrepancy between observed and predicted numbers of trips and to gauge the stability and robustness of estimates. This challenge is taken up in section 3.1.

2.2 Choice Models

Numerous decisions are made when consumers go shopping. Many of these decisions refer to the scheduling and timing of activities. Some consumers prefer to shop during the morning, others buy goods during their lunch-hour or on their way home from work.

Store managers have an interest in these decisions, especially when they are planning shop opening hours, staffing levels and ease of customer flow through the store and at the checkouts. Peak demand in the foodhall of a central department store occurs during the lunchtime on weekdays, whereas at a suburban superstore peak demand arises late Friday afternoon and on Saturdays. Urban planners also need to monitor the decisions made by shoppers, so that car parks and traffic flows can be managed efficiently.

2.2.1 Logistic Regression

Example 2 Early Evening Shopping

In the current example we predict the probability that consumer i chooses to shop during the early evening p_i or not $1-p_i$. There are $i = 1,2, \ldots, N$ individuals, where N = 304 Cardiff shoppers who are observed over one week. Early evening is defined as any time after 4 pm.

Typically a consumer leaves work or another afternoon activity, and on the route home grocery goods are bought. All these trips are destined for the home, but they may originate anywhere in the city. For about 20% of consumers this form of shopping behaviour is important.

Many observed variables are of possible significance; though two stand out. Firstly, the role of employment is expected to be relevant. The journey home from work is likely to present many opportunities for convenience shopping and may be the only discretionary time period available in a busy day. The employment factor explains why proximity to home is not always a good predictor of shop choice, and that nearness to a route between home and workplace is more relevant. Here the variable EMPL is defined as the percentage of a household in part-time or full-time employment.

Disposition is the second factor expected to be influential. Many elderly and young persons with children prefer to shop during the morning; a point stressed by Hillman et al. (1976) in their study of mobility among housewives, teenagers and pensioners, and confirmed by data from Cardiff (chapter 2). We would expect a negative relationship between these types of consumer and early evening shopping. For these reasons several measures of the life-cycle are incorporated within the logit model.

The variable AGEG is defined as an ordinal attribute starting at 16 years and extending to 65 years in 7 stages. Almost 32% of the sample fall within the category 25 to 34 years. Household size, HHOD, is observed too and we note that in most large households (where there are children) there is a non-working mother whose disposition is to shop in the morning (when children are at school) or on Saturday (when the whole family can assist).

A model that includes the variables HHOD, AGEG and EMPL is estimated:

$$\ln\left[p_i/(1-p_i)\right] = \underset{(0.5)}{-0.44} \underset{(2.2)}{-0.32}\ HHOD_i \underset{(6.3)}{+0.04}\ EMPL_i \underset{(2.8)}{-0.04}\ AGEG_i$$

df = 300   deviance D = 229   chi-square χ^2 = 292

where asymptotic values of the t-statistics are in parentheses.

Signs and parameter estimates have logical interpretations. Early evening shopping is unlikely among those who supervise children in large households. Retirees have the time and predilection to shop early in the day, so advancing age has a negative sign. Employment raises the probability of shopping during the early evening, possibly in conjunction with the homeward journey. Parameter estimates for EMPL and AGEG are significant at 99% and HHOD at 95%.

Not included is a reference to shopping possibilities; for instance one might envisage an indicator of how easy it is to interrupt a journey home from work when rush-hour parking restrictions are imposed. Such a variable would take into account the provision of car parks and the location of transfer points on the public transport system, neither of which are easily measured.

The term $\ln\left[p_i/(1-p_i)\right]$ expresses the log odds that the revealed behaviour of individual i will be the choice of early evening shopping. More meaningful are the expected probabilities of choosing early evening shopping, these are calculated from the logit function and illustrated in table 2.2. Six household types are defined from the three observed variables. In households 1 to 3 age is held constant and we see how an increasing percentage of the household in paid work raises the expected probabilities. Members of a large household (type 4) and aged shoppers (in types 5 and 6) reveal low expected probabilities.

Overall goodness of fit measures are analogous to those used in conventional and poisson regression. Values for the likelihood ratio ρ^2 are calculated, to give 0.26. Values lying between 0.2 and 0.4 are regarded as good fits in the discrete choice literature, so the model presented here is acceptable. Just to consider overall goodness of fit, however, is insufficient and in section 3.2 attention is turned to the assessment of logit models.

Table 2.2

A Logit Model of Early Evening Shopping:
Six Household Types

Household type	Household size (number)	Percentage employed (% of family)	Age of shopper (groups)	Expected probability of choosing to shop early in the evening
1	1	0	2	0.30
2	2	50	2	0.70
3	2	100	2	0.94
4	6	33	3	0.24
5	3	33	6	0.42
6	2	0	6	0.21

2.3 Daily Shopping Models

The space-time sequencing of trips and events has been a prime concern of activity modellers. This can be studied at various resolutions, and the chaining of activities is one detailed example. Broader in scope are studies of diurnal, daily and weekly trip incidence. Attempts to model these broader patterns are found in the work of Damm and Lerman (1981), Landau et al. (1981) and Damm (1982); most of these studies are set in the context of discrete choice theory.

Example 3 Poisson Models of Daily Shopping Incidence

Here a daily count is made of grocery trips. Incidence on each day of the week describes a poisson distribution with typical features (ie. many zeros, a long tail and a low mean). We aim to predict the mean number of shopping trips on each day given data for observed variables. Apart from the calculation of mean participation rates, a comparison is made of estimates.

Results are tabulated in table 2.3, one model being shown on each row. Some informative findings are revealed by the parameter estimates. Deep freezer ownership (DFEZ) discourages heavy trip incidence, this is particularly true for Monday. People who have lived in the area for a long time (RESD) or who live in larger households (SIZE) undertake more trips, especially early in the week. Whatever the day, advancing age (AGEG) increases the predicted number of trips.

Other variables refer to work status (WORK), car availability (AVAL), and attitudes, namely whether parking is important (PARK), whether there is a preference for shopping just once a week (ONCE), and whether there is an attempt to do shopping quickly (KWIK). Overall there are 10 variables and 6 are used each day, in each case specific choices depend on the relevance of particular variables.

While informative, the utility of these findings is limited. Generally t-statistics are low and fluctuate, so too are measures of goodness of fit (table 2.4). Likelihood ratios are higher over the period Monday to Wednesday, thereafter they decline. On grounds of parsimony the null model - where all variation in the data is ascribed to the random component - may be just as acceptable in a few cases. However, there are reasons to do with management, marketing and planning which suggest that observed variables need to be retained.

For example, the success of late-night or weekend opening depends on the nature of the catchment area, the specific location and other observables. Just such decisions are being made by managers at Mace Line (who are planning to open 'Convenience Express' shops) and at Neighbourhood Stores (who are introducing into Britain the American-style '7-Eleven' stores). All these stores open early in the morning, stay open late at night and operate 7 days a week. Success in these cases depends on suburban locations near tube stations and bus transfer points.

Table 2.3

Daily Incidence of Grocery Shopping:
Parameter Estimates for Six Poisson Regression Models

Day of Week	Constant	SIZE	PARK	DFEZ	RESD	AGEG	ONCE	WORK	AVAL	KWIK	INCO
	(a) Parameter Estimates										
Monday	-1.30	0.21	-0.09	-0.50	0.47					0.16	-0.09
Tuesday	-2.10	0.24	0.12	-0.29	0.13					0.02	-0.10
Wednesday	-2.73	0.26		-0.24		0.01	0.18			0.10	-0.05
Thursday	-1.63	0.15				0.01	0.08	0.13		0.06	-0.04
Friday	-2.26	0.18			0.03	0.01	0.10			0.05	0.05
Saturday	-1.33	0.18		-0.25		0.01			0.12	0.08	-0.02
	(b) t - Statistics										
Monday	2.0	3.6	1.1	2.7	0.7					2.2	1.5
Tuesday	3.2	4.4	1.5	1.7	1.9					0.3	1.7
Wednesday	4.1	3.8		1.3		1.3	1.9			1.2	0.9
Thursday	3.0	2.6				1.4	1.1	0.9		0.8	0.9
Friday	4.0	3.3			0.5	1.3	1.3			0.8	1.1
Saturday	2.7	3.3		1.7		1.5			0.8	1.4	0.3

Note: Abbreviations are defined in the text.

Table 2.4

Daily Incidence of Grocery Shopping:
Goodness of Fit for Six Poisson Regression Models

Goodness of Fit		Days of the Week					
		Mon	Tues	Wed	Thur	Fri	Sat
Log-likelihood, constants only	L_O	234	239	238	222	236	215
Log-likelihood at convergence	L_{max}	208	210	213	211	219	198
Degrees of freedom	df	297	297	297	297	297	297
Chi-square	χ^2	181	183	197	163	177	147
Likelihood ratio index	ρ^2	.11	.12	.10	.05	.07	.08

At a detailed resolution poisson-regression models provide informative findings (example 1); but they are less suitable for the broad analysis of daily incidence (example 3). Similar conclusions were reached when logit models of daily shopping choice were estimated. Several courses of action follow from these studies. Model assessment needs to be given greater attention, including an appraisal of parameter estimates (sections 3.1 and 3.2). Assessment leads to a search for sounder models; these models ought to be robust to minor changes in data (section 3.3). More fundamentally, there is a need for model reformulation and a shift away from comparative statics towards temporal and dynamic specifications (chapter 5).

3 Assessment of Incidence and Choice Models

Quantitative analysis in the social sciences is tending to shift away from confirmatory and inferential statistics. Instead, exploratory approaches are being fostered. These exploratory approaches are concerned with data description, robust modelling and empirical generalisation. All exploratory approaches stress the creative interaction between data, model and analyst, an interaction that has become far more routine because of modern computer power.

An important element of these new approaches is the diagnostic testing of models. Diagnostics identify areas of reliability and deficiency in a model, they give us confidence in the findings or show where refinements are needed most. The aim then is to estimate a model that is more resilient or robust, such a model will be less affected by erroneous data and more likely to generalise when new data are presented.

Regression residuals hold the key to the construction of most diagnostics. Least-squares residuals are easily obtained in conventional regression and these have formed the basis of work by Belsley et al. (1980), Huber (1981), and Cook and Weisburg (1982). This form of model assessment is now routine and all the standard statistical packages automatically display diagnostics.

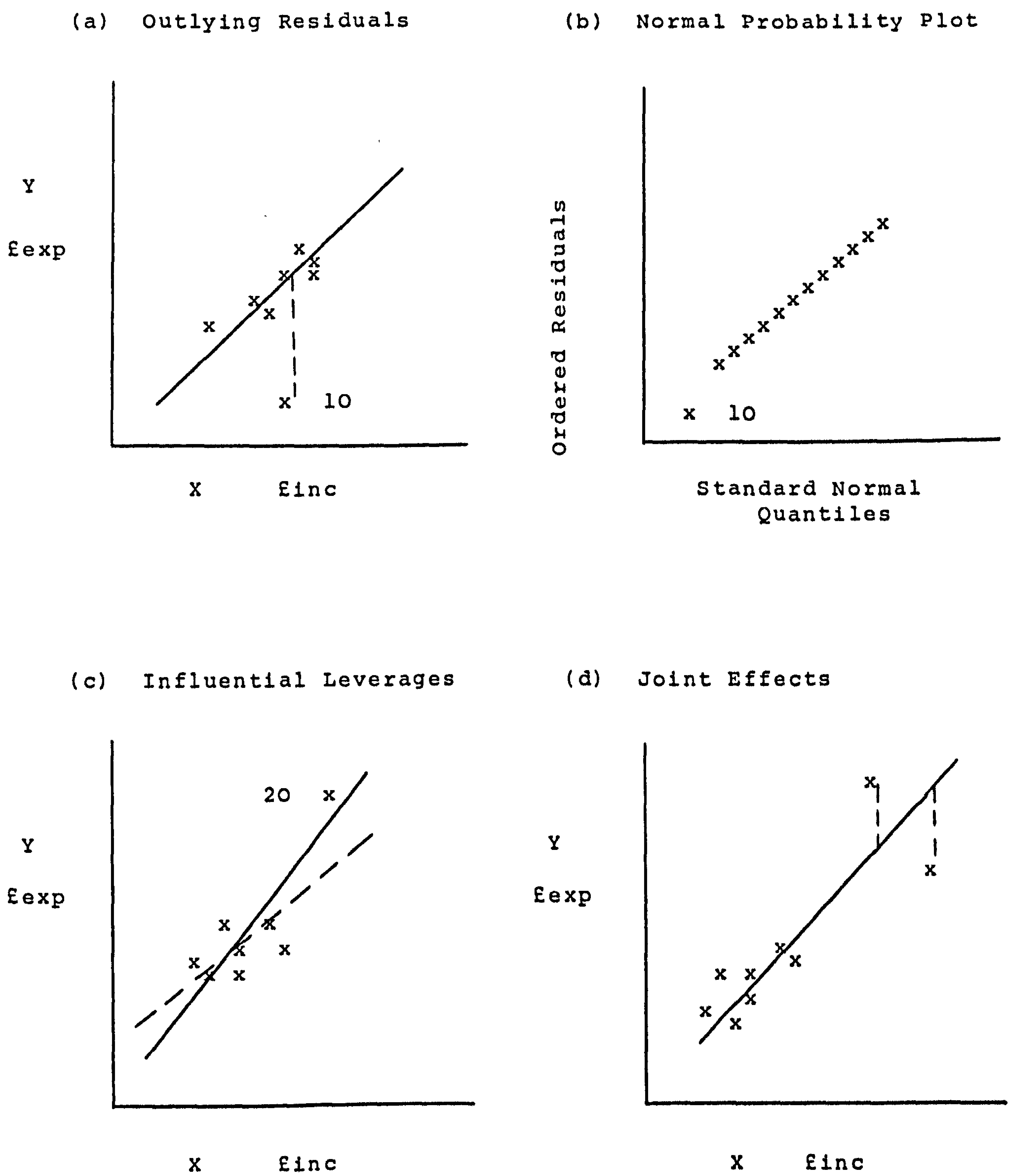
The situation for non-normal regression is very different. Theoretically all members of the exponential family of statistical distributions can be tested in an analogous fashion, so diagnostic tests should be widely available. In practice the software has not existed to popularise non-normal diagnostics and the identification of 'residual-like' terms is not always easy.

Qualitative response models - logit, probit and tobit - were the first to offer up some solutions and Cox and Snell (1968) were able to define 'general residuals'. The search for diagnostics in qualitative response models has been advanced by Pregibon (1981, 1982, 1984). To operationalise his work, Pregibon has used the general linear modelling framework that is available with the GLIM statistical package (Baker and Nelder 1978, see also McCullagh and Nelder 1983). It is possible to fit any member of the exponential family of distributions and write macros to obtain most of the diagnostics.

In the examples that follow diagnostics for logit regression are presented. These are derived from the work of Pregibon, and an extension is made to the case of poisson regression. We then investigate how these models of incidence and choice might be refined. Before looking at these models and refinements a very brief review of conventional diagnostics is given.

Figure 3.1

The Principles of Regression Diagnostics



The basic principles are best explained by reference to an example and some simple plots (figure 3.1). In a study of consumer expenditure the amount of money spent by a household is a function of the net disposable income. For household i, expenditure y_i is the response, and disposable income, x_i, is the independent observed variable. This single independent observed variable defines a trivial covariate space.

A linear regression model is estimated, the fit from which is described by the diagonal line in (a) of figure 3.1. Associated with each individual is a residual, this value is the discrepancy between the observed response and the fitted value estimated from the regression model. On the whole, residuals are small (by virtue of the least-squares criterion). However, the residual for household 10 lies apart from the others. Empirically, household 10 reveals exceptionally low expenditure given its high disposable income. Perhaps money is being channelled into savings or gambling rather than spent on consumer goods; for whatever reason the fitted value is a poor predictor of the observed response.

If all residuals are placed in order of magnitude they should describe a normal distribution. This is seen in figure 3.1(b) where ordered residuals are placed against standard normal quantiles. A straight-line describes a perfectly normal distribution, so any significant departures are associated with anomalous points. Household 10 does not conform and appears as a 'long tail'.

There may be points which lie close to the regression line in covariate space, yet exert undue influence because they are beyond the main cluster of points. In fact all points will exert some (minor) influence on estimation, but if there are a few exceptionally influential points then estimation of parameters may be distorted. Figure 3.1(c) depicts a situation where the 'leverage' of household 20 bends the whole regression line from the true slope (dotted line). Household 20 has such a disproportionate influence because of exceptionally high income and expenditure.

High leverage points are rarely large residuals, but joint effects will be exhibited on some occasions and it is important to measure these. Such a case is shown in figure 3.1(d). Under these circumstances it is important to separate out the different effects before taking any corrective action.

Conventional regression now has a suite of tests to diagnose all the features shown in figure 3.1. The most important tests are derived from standardised residuals, leverage values and joint measures such as Cook's distance. All these have been applied to the study of consumer spending in Cardiff, however here we only consider examples where y_i is not measured along a continuous scale.

3.1 Incidence Models

Example 1 Family Maintenance Activities and Shopping (Revisited)

Recall that in example 1 of this chapter a poisson model was fitted to trip incidence data. The incidence of chained activity, involving both shopping and family maintenance, was modelled from observations about the number of children in each family, work status and household income. Maximum likelihood estimates were obtained and the global goodness of fit was noted. Now the model is assessed.

Firstly a method to identify extraordinary observations is outlined, and then model sensitivity to these observations is measured. Discussion of these topics also is to be found in Dunn and Wrigley (1984a) and Uncles (1984a).

3.1.1 Detection of Outlying and Unduly Influential Observations

Central to the detection of outlying and unduly influential observations is the idea that aggregate measures of fit can be disaggregated into individual constituents, and that these constituents are like residuals. Once we have values that are 'residual-like' the full set of diagnostics can be extracted from poisson regression models.

Two sources of diagnostic material are available: (a) measures of the discrepancy between observed and predicted responses (residuals), and (b) the amount of influence exerted by an individual in the space defined by independent observed variables (leverage). Special interest is given to outlying residuals and influential leverages, and their impact on model estimates.

(a) Outlying Residuals

In poisson regression the components of chi-square and components of deviance are analogous to the residuals of conventional regression. Chi-square and deviance, themselves, are global measures of fit. From Nelder and Wedderburn (1972, 375):

$$\chi^2 = \Sigma(y_i - m_i)^2/m_i$$

and

$$D = 2\{\Sigma y_i \ln(y_i/m_i) - \Sigma(y_i - m_i)\}$$

where y_i are responses and m_i is the predicted mean for individuals $i = 1,2, \ldots, N$. Disaggregation into components χ_i and d_i follows from the removal of summations:

$$\chi_i = (y_i - m_i) / m_i$$

and

$$d_i = \pm\surd\{2|y_i \ln(y_i/m_i) - y_i + m_i|\}$$

Therefore, as with conventional standardised residuals, large component values of χ_i and d_i highlight discrepant points.

Plots of χ_i and d_i versus household index values are shown in figure 3.2. A majority of observations are well within the range ±2 (an arbitrary figure), although about 14 χ_i and 8 d_i exceed 6 on the scale of component values. All these are substantial under-predictions of m_i given observed responses y_i.

Most serious of the outliers is number 21 (χ_i is almost 17 and d_i is about 8). Because there are no children in the family and the consumer works (restricting time for family maintenance) the predicted number of chained trips is approximately one, yet 18 chained trips are actually undertaken. Inspection of attitudinal data shows that this consumer attempts to combine grocery shop visits with other errands.

Other large residuals are associated with households 122 and 126; observed numbers of chained trips (20 and 13 respectively) are both higher than expected given these consumers' relatively low income and fewer than average number of children.

During the assessment of conventional regression it is usual to produce normal probability plots of residuals. For poisson models these need to be treated more cautiously. Plots of ordered residuals and ordered chi-square values, both placed against the vector of normal deviates, are depicted in figure 3.3. Two things are revealed: (1) a J shaped curve, describing a substantial positive skew, which re-states that the underlying sampling distribution is poisson, and (2) outliers that stand apart from the mass of values. Observation 21 stands out as an under-prediction whilst 243 is a notable over-prediction (m_i equals 10 yet no trips are actually recorded).

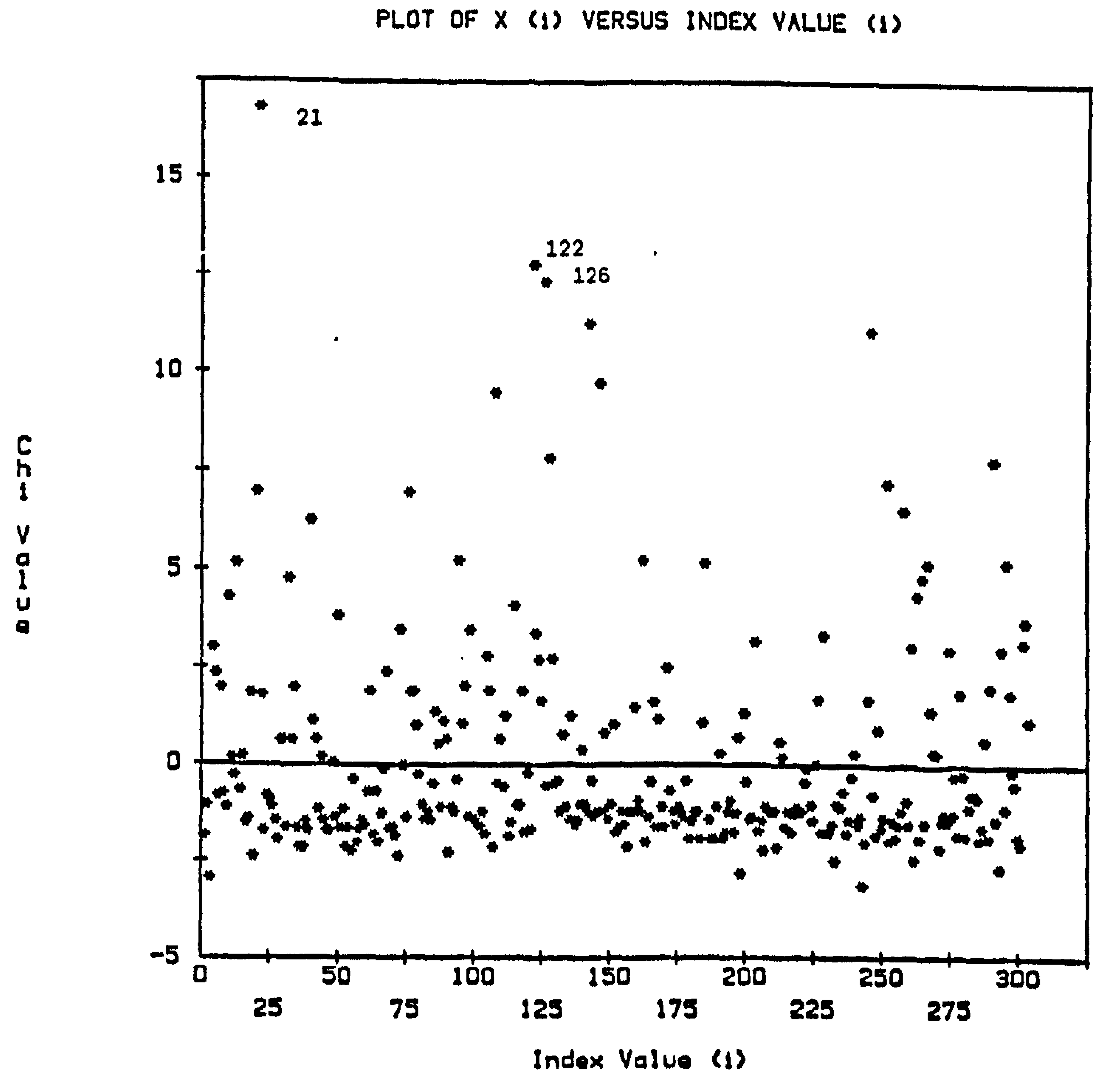
(b) Influential Leverages

Leverage refers to the amount of influence that an individual observation has in the space defined by independent variables. Initially the least-squares procedure is derived, then an extension is made to poisson regression and leverages are extracted.

First the covariate space is defined from least-squares estimates:

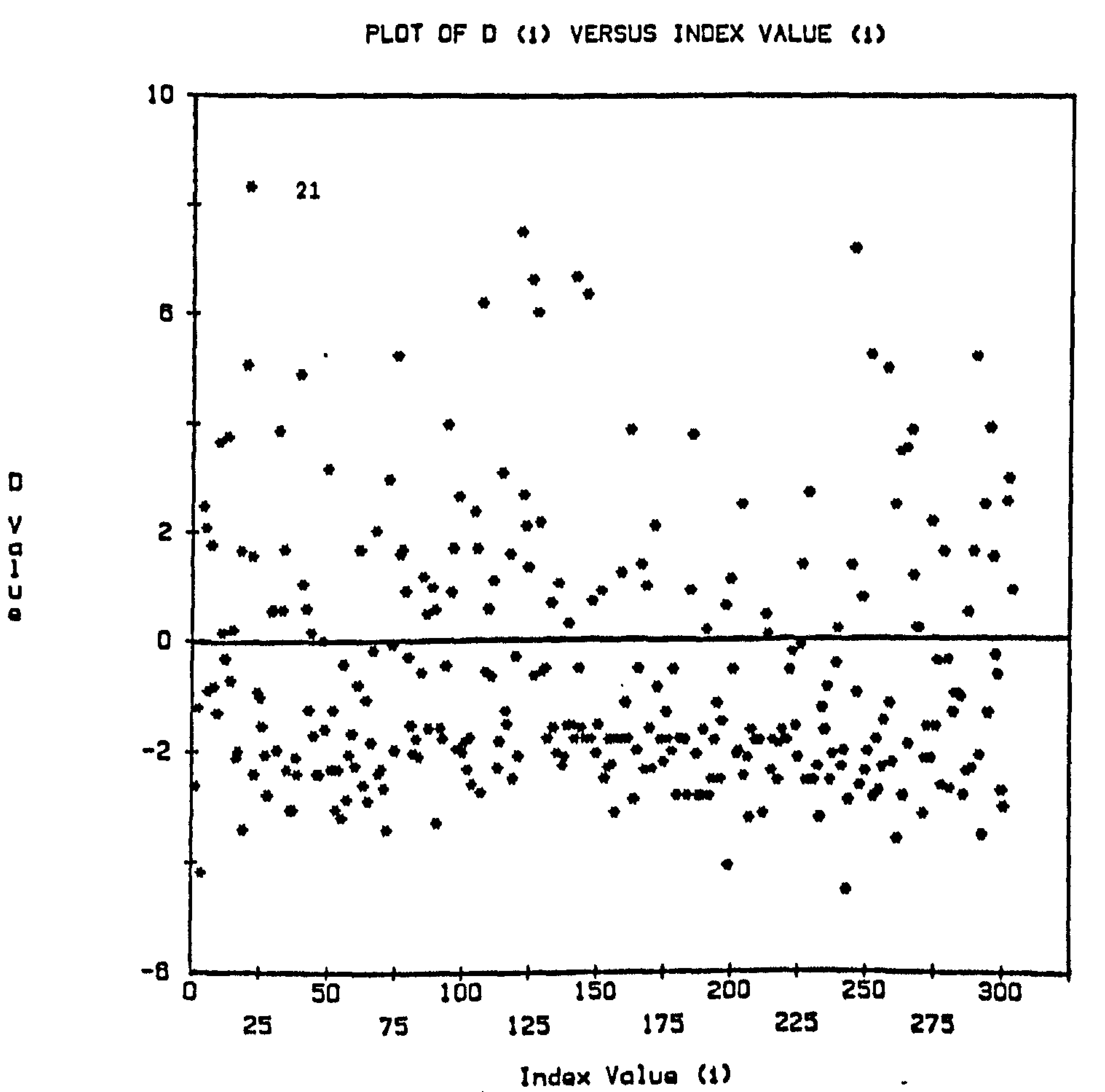
$$\hat{\underset{\sim}{y}} = \underset{\sim}{X}(\underset{\sim}{X}'\underset{\sim}{X})^{-1}\underset{\sim}{X}'\underset{\sim}{y}$$

where $\hat{\underset{\sim}{y}}$ is a N * 1 vector of fitted values
$\underset{\sim}{y}$ is a N * 1 vector of response values
$\underset{\sim}{X}$ is the N * K matrix of independent observed values
and $(\underset{\sim}{X}'\underset{\sim}{X})^{-1}\underset{\sim}{X}'\underset{\sim}{y} = \underset{\sim}{\beta}$ are maximum likelihood estimates



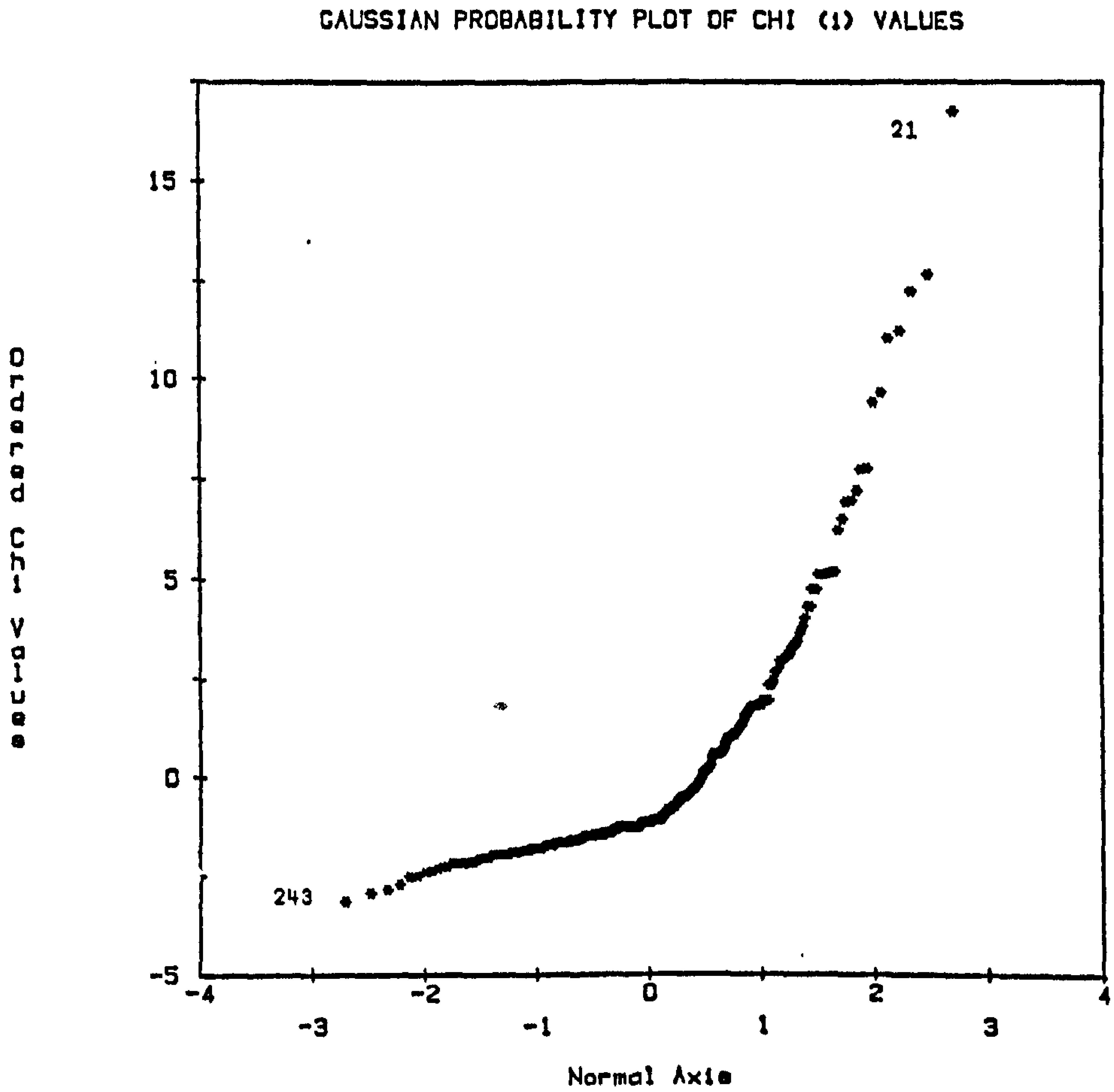
Figure

3.2 (a)



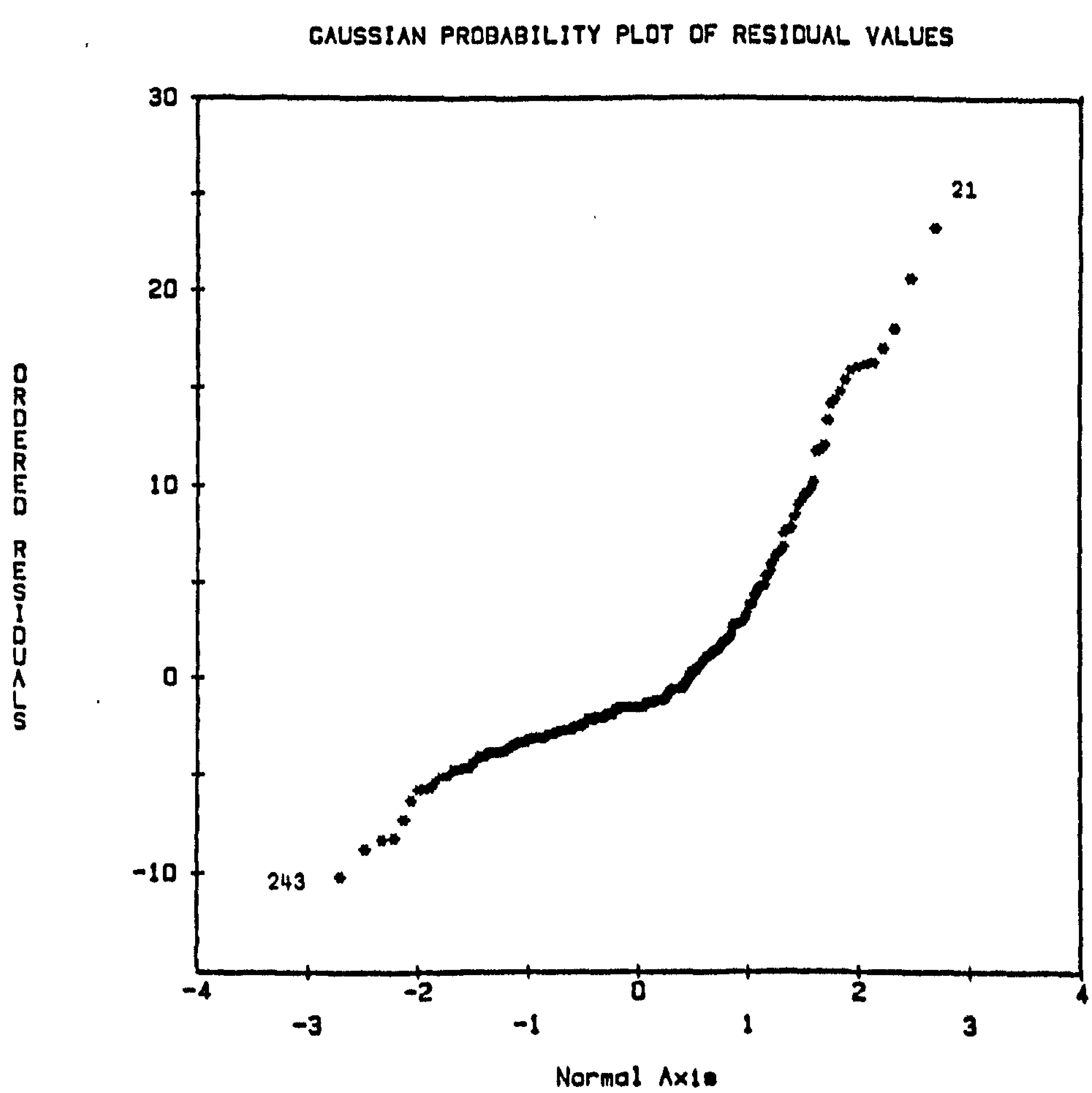
Figure

3.2 (b)



Figure

3.3 (a)



Figure

3.3 (b)

The projection matrix follows from a mapping of observed responses and fitted values in the covariate space:

$$\hat{\underset{\sim}{y}} = \underset{\sim}{H}\,\underset{\sim}{y}$$

where H is the 'hat' matrix with terms $\underset{\sim}{X}(\underset{\sim}{X}'\underset{\sim}{X})^{-1}\underset{\sim}{X}'$ and the projection is:

$$\underset{\sim}{M} = \underset{\sim}{I} - \underset{\sim}{H} = \underset{\sim}{I} - \underset{\sim}{X}(\underset{\sim}{X}'\underset{\sim}{X})^{-1}\underset{\sim}{X}'$$

The diagonal elements of $\underset{\sim}{H}$, denoted h_{ii}, are the leverage measures of conventional regression analysis.

In the case of poisson regression the projection matrix is determined from predicted means m_i (not fitted values $\hat{y}_i$ - recall that the '^' notation is not being used for poisson and logit models) and the beta estimates are obtained using the method of iterative re-weighted least-squares. The covariate space is now:

$$\underset{\sim}{m} = \underset{\sim}{V}^{\frac{1}{2}}\underset{\sim}{X}(\underset{\sim}{X}'\underset{\sim}{V}\underset{\sim}{X})^{-1}\underset{\sim}{X}'\underset{\sim}{V}^{\frac{1}{2}}\underset{\sim}{y}$$

where $\underset{\sim}{m}$ is a N * 1 vector of predicted means
$\underset{\sim}{y}$ is a N * 1 vector of response values
$\underset{\sim}{X}$ is the N * K matrix of independent observed values
$\underset{\sim}{V}$ is a N * N matrix whose diagonal elements, v_{ii}, equal the predicted means m_i
and $(\underset{\sim}{X}'\underset{\sim}{V}\underset{\sim}{X})^{-1}\underset{\sim}{X}'\underset{\sim}{V}^{\frac{1}{2}}\underset{\sim}{y} = \beta$ are iterative re-weighted least-squares estimates

The associated mapping is:

$$\underset{\sim}{m} = \underset{\sim}{H}\,\underset{\sim}{y}$$

where H is the modified hat matrix given by $\underset{\sim}{V}^{\frac{1}{2}}\underset{\sim}{X}(\underset{\sim}{X}'\underset{\sim}{V}\underset{\sim}{X})^{-1}\underset{\sim}{X}'\underset{\sim}{V}^{\frac{1}{2}}$. Dunn and Wrigley (1984a) show that the projection matrix becomes:

$$\underset{\sim}{M} = \underset{\sim}{I} - \underset{\sim}{H} = \underset{\sim}{I} - \underset{\sim}{V}^{\frac{1}{2}}\underset{\sim}{X}(\underset{\sim}{X}'\underset{\sim}{V}\underset{\sim}{X})^{-1}\underset{\sim}{X}'\underset{\sim}{V}^{\frac{1}{2}}$$

The diagonal elements of $\underset{\sim}{H}$ have an interpretation similar to that given before; ie. values of h_{ii} which depart significantly from zero are points of leverage worthy of special attention.

Individual h_{ii} values are plotted in figure 3.4 against household index numbers. Within the covariate space the influence of a single individual is unlikely to be large, indeed the average leverage is 0.01. Using the threshold criteria recommended by Belsley et al. (1980), of 2K/N and 3K/N, 6 observations are found to exceed 3K/N and a further 16 lie between these two

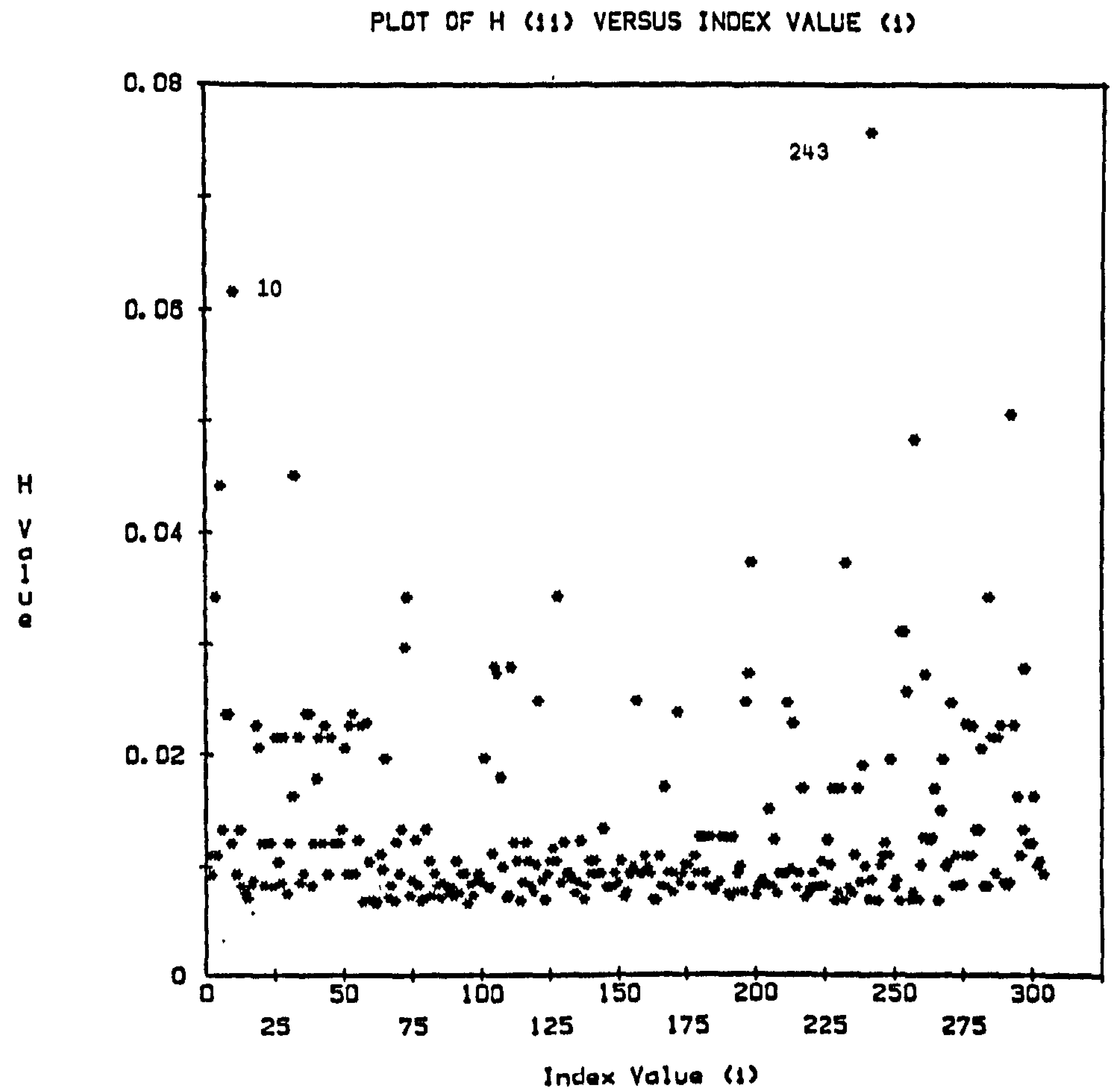


Figure 3.4

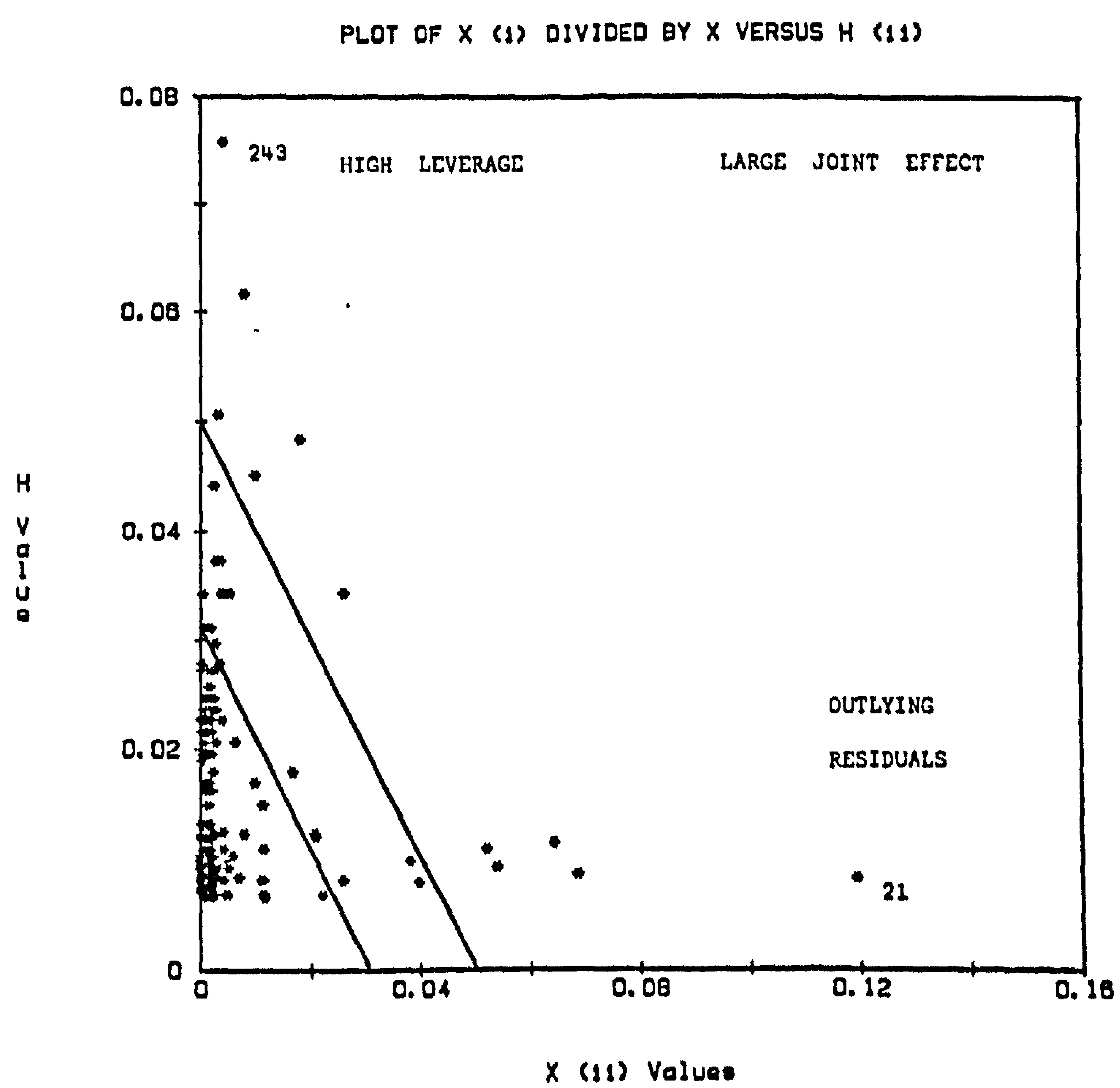


Figure 3.5

thresholds. Greatest leverage is associated with households 243 and 10, these score highly on the income scale and have large families. The concentration of high leverages around household 250 is associated with a number of families living on the Llanedeyrn estate in north Cardiff, each of which has four or more children, a level which far exceeds the sample average of about one.

It is now possible to bring together outliers and leverages. Pregibon (1981, 712) presents a helpful plot in which leverages (h_{ii}) are added to components of chi-square that have been adjusted by the value of chi-square (χ_i^2/χ^2). The joint effect is denoted by h_{ii}^*.

$$h_{ii}^* = h_{ii} + \chi_i^2/\chi^2$$

The modified diagonal elements of the hat matrix, h_{ii}^*, have values that lie between one and zero, and an average of:

$$\text{ave}(h_{ii}^*) = (K + 1)/N$$

A plot, using leverages and modified components of chi-square, exposes the joint effect. Drawn across figure 3.5 are contours which correspond to thresholds at $2*\text{ave}(h_{ii}^*)$ and $3*\text{ave}(h_{ii}^*)$. Eleven points lie above the top threshold: on the residual axis household 21 is outstanding, while the point nearest unity on the leverage axis corresponds to consumer 243. Few observations occupy the central space which suggests that the diagnostics are exposing essentially different aspects of poor fit.

3.1.2 The Sensitivity of Model Parameters to Outlying and Unduly Influential Observations

Analysis of the sensitivity of parameter estimates and fitted values helps the analyst to assess whether the model is over responsive when single data points are deleted or when minor perturbations have a significant impact on (a) parameter estimates and (b) fitted values. To make this check a number of sensitivity measures are used, these are based on the deletion of successive observations.

The underlying principle is similar throughout, where individual observations are available the measure of sensitivity is:

$$\Delta_i\text{FIT} = \text{FIT(all observations)} - \text{FIT(all observations except i)}$$

Conventional regression presents few difficulties since 'FIT(all observations except i)' is derived exactly from least-squares estimation, in other circumstances approximations have to be used.

(a) The Sensitivity of Estimated Beta Parameters

Observation i is deleted from the estimation of each beta term. When deletion is repeated for $i = 1,2,\ldots,N$ the pattern of sensitivity is traced. In conventional regression successive observations are deleted from the least-squares estimates of $\underset{\sim}{\beta}$ and the difference between modified and original estimates is compared:

$$\text{DBETA}_i = \underset{\sim}{\beta}(\text{all observations}) - \underset{\sim}{\beta}(\text{all observations except } i)$$

Exactly the same principles hold true for poisson regression. Dunn and Wrigley (1984a) suggest that the previous expression becomes:

$$\text{DBETA}_i = (\underset{\sim}{X}'\underset{\sim}{V}\underset{\sim}{X})^{-1}\underset{\sim}{x}_i\ (y_i - m_i)/(1 - h_{ii})$$

where $(\underset{\sim}{X}'\underset{\sim}{V}\underset{\sim}{X})^{-1}$ is the inverse of the cross-product matrix used to determine the iterative re-weighted least-squares estimates

$\underset{\sim}{V}$ contains diagonal elements $v_{ii} = m_i$

$\underset{\sim}{x}_i$ is a vector of observed variables for individual i

$(y_i - m_i)$ is the residual between observed and predicted values for i

and $1-h_{ii}$ are diagonal elements of the projection matrix

For a particular beta term, denoted β_k, and standardising, we have:

$$\text{DBETA}_{ik} = \frac{\beta_k(\text{all obs}) - \beta_k(\text{all obs except } i)}{\text{standard error}\left[\beta_k(\text{all obs})\right]}$$

Depicted in figure 3.6(a) is a DBETA_{ik} plot for the number of children (β_1 CHILD) versus household index numbers. Values exceeding one standard error are moderately important so observation 258 stands out. Removal of this single case would reduce the estimate β_1 by 1.28 standard errors, although the estimate would remain significant at 95%.

The overall impression is equivocal since three other large values in figure 3.6(a) are negative - 32, 143 and 243 - the omission of these would substantially increase estimates of β_1.

Least sensitive to the deletion of individual observations is the estimate for work status (β_2 WORK). Whereas the income parameter estimate appears to be more sensitive, in fact the removal of observations 21, 122 and 126 would raise estimated β_3 INCO a lot. All these households have low incomes given their moderately high levels of trip incidence.

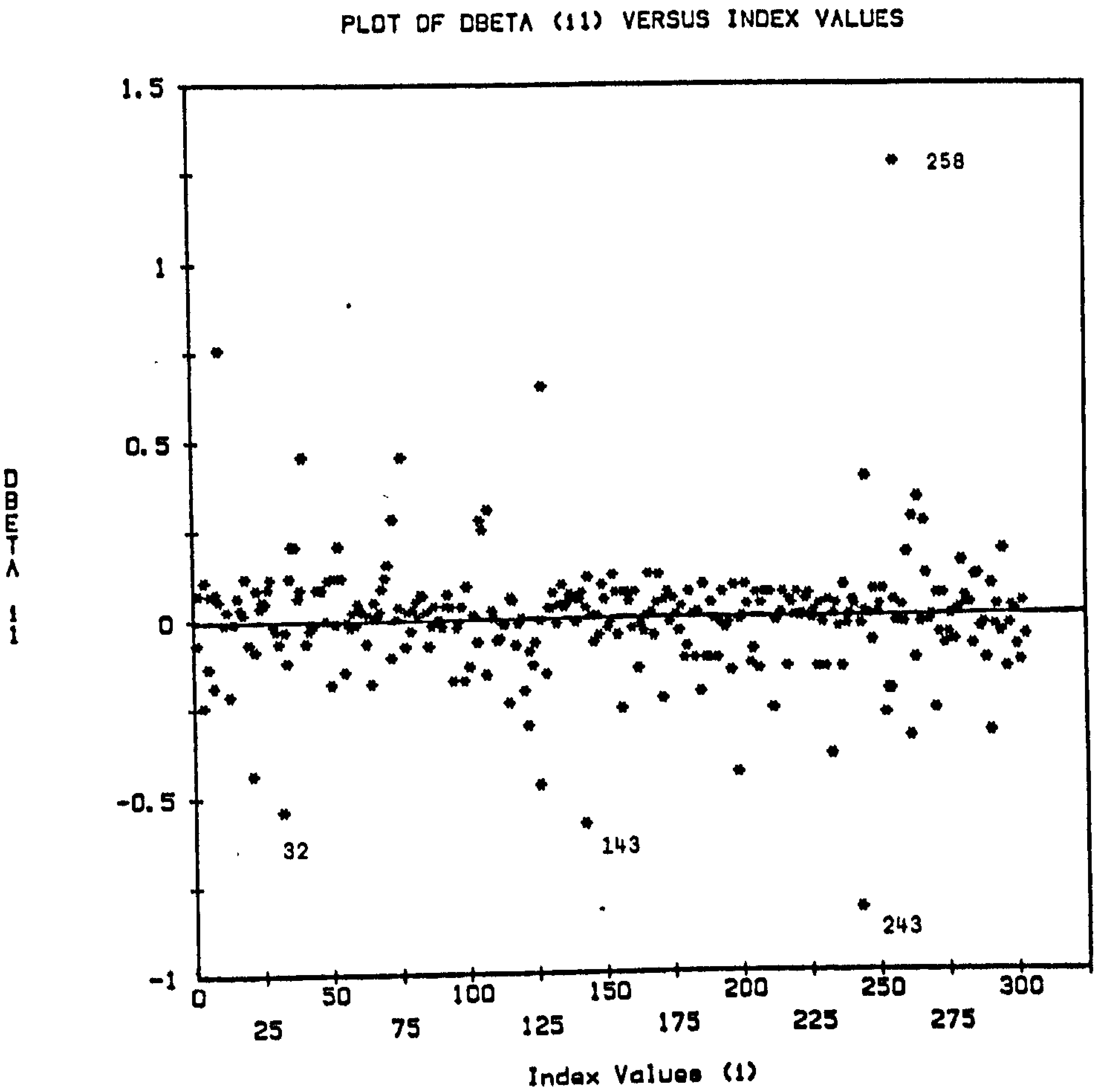


Figure 3.6 (a)

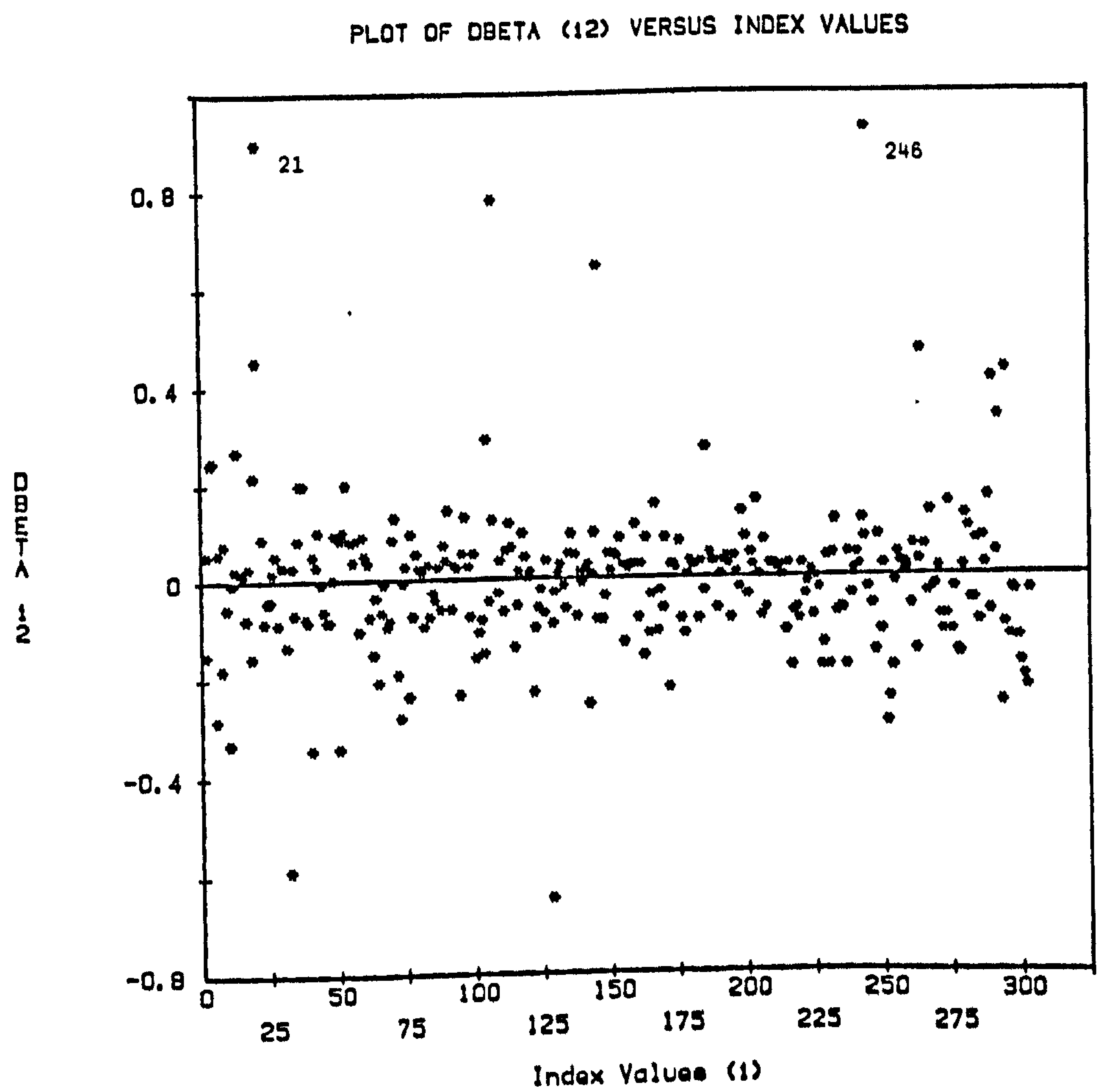


Figure 3.6 (b)

PLOT OF DBETA (13) VERSUS INDEX VALUES

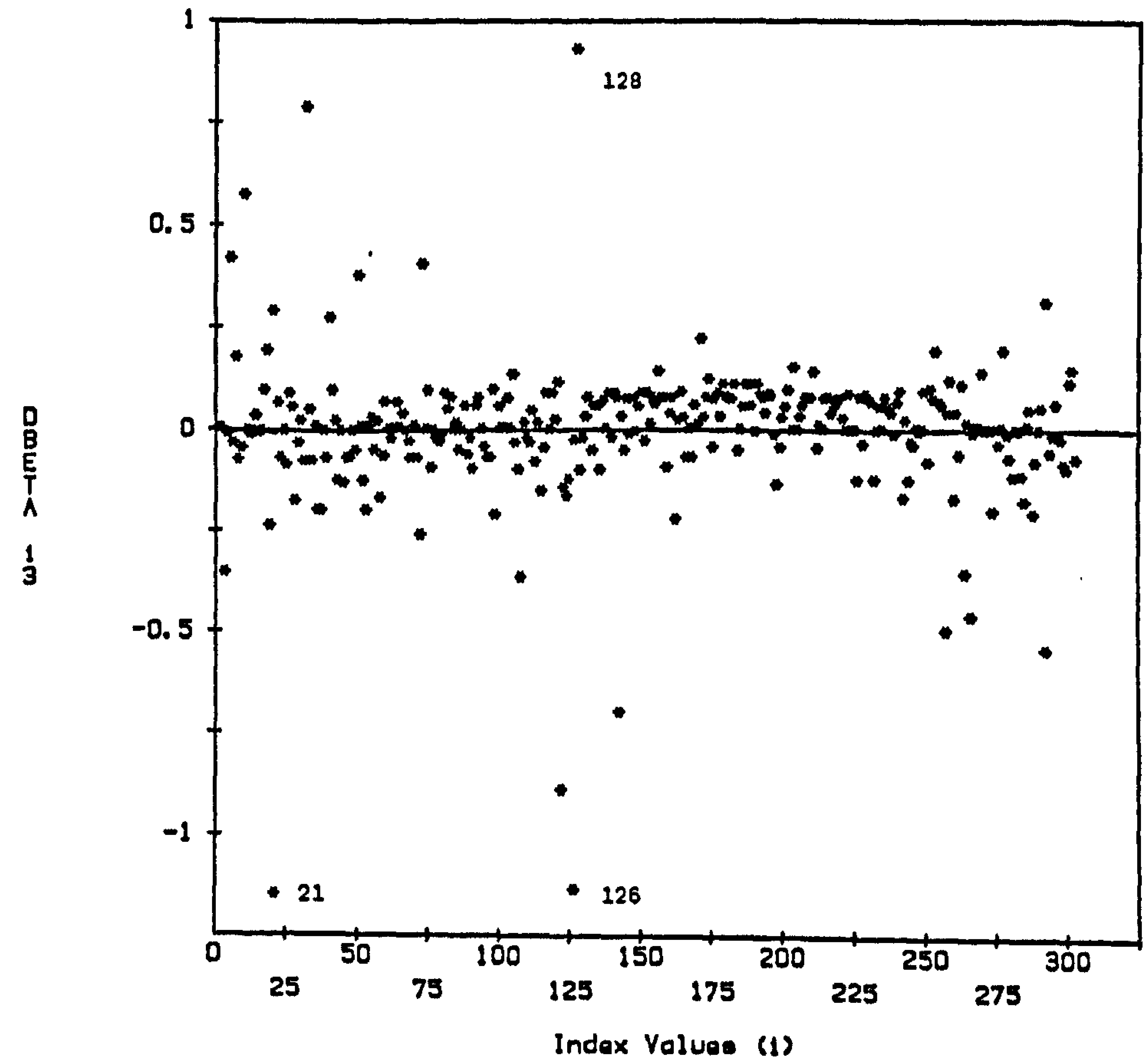


Figure 3.6 (c)

PLOT OF DFIT (i) VERSUS INDEX VALUES

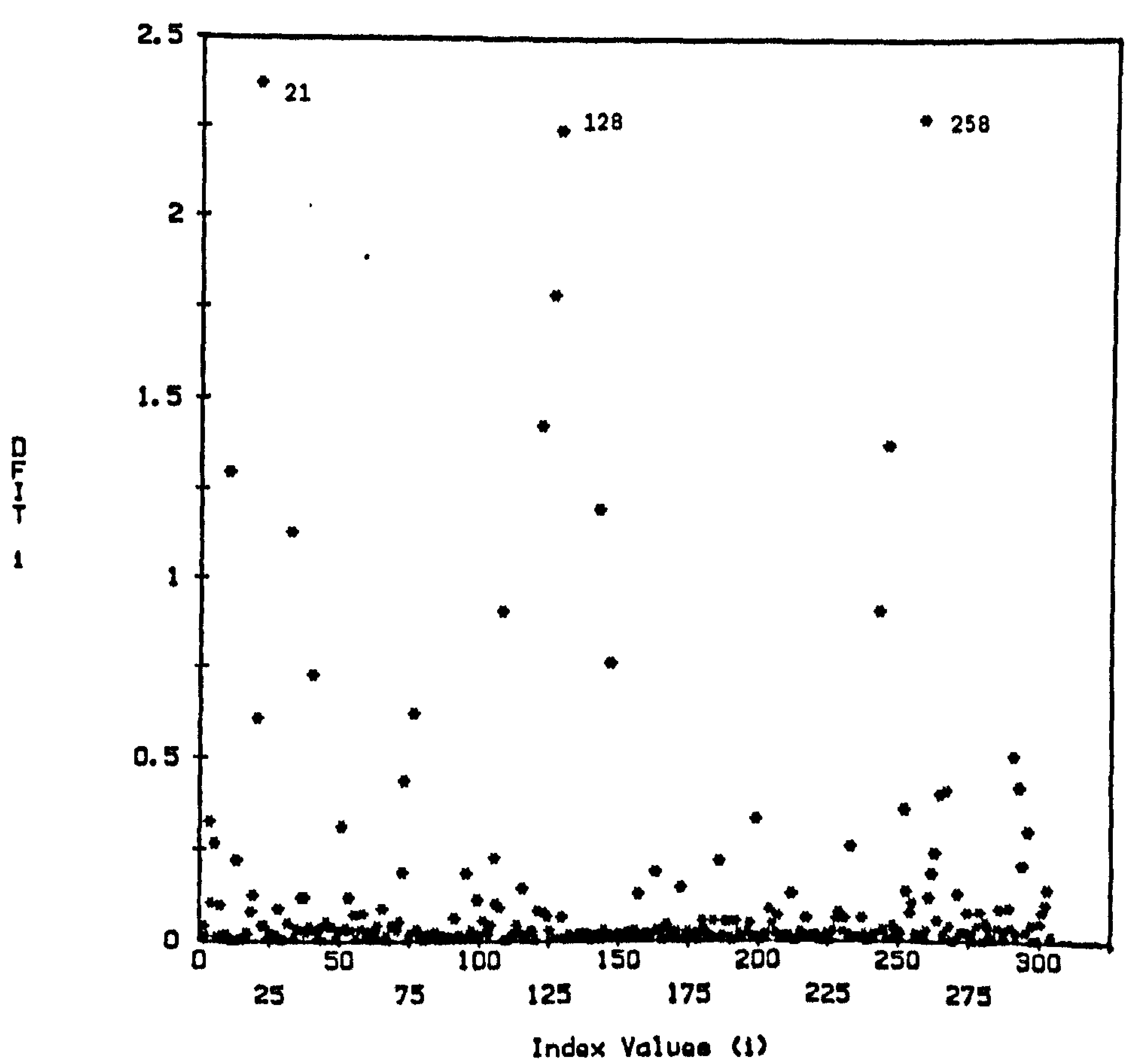


Figure 3.7

Table 3.1

Family Maintenance and Shopping:
the Stability of Parameter Estimates

Household number	Values of $DBETA_{ik}$ CHILD	WORK	INCO	Cause of instability
10	0.76		0.58	L
21		0.90	-1.15	R
32	-0.54	-0.59	0.79	R & L
122			-0.89	R
126			-1.14	R
128	0.65	0.65	0.94	R & L
143	-0.58		-0.70	R
147		0.64		R
243	-0.82			L
246		0.92		R
258	1.28			R & L
298			-0.54	L

Only major effects are shown (ie. those where $DBETA_{ik}$ > ±0.5 of a standard error).
Negative signs indicate that the removal of household i would raise the value of β_k; positive signs indicate the converse.

L significant leverage, low residual
R significant residual, low leverage
R & L significant joint effect

Table 3.1 is a list of data points which cause significant shifts in parameter estimates. Standardised $DBETA_{ik}$ values are shown and against each value the cause of instability is stated. High values are ascribed to influential leverages or to outlying residuals, and in a few cases there is a joint effect. The $DBETA_{i1}$ plot is most affected by high leverages, whereas high residuals underlie the instability that is revealed by plots of $DBETA_{i2}$ and $DBETA_{i3}$.

(b) The Sensitivity of Fitted Values

The impact on fitted values is assessed from a deletion technique too (Pregibon 1981, 718,and Dunn and Wrigley 1984a). Conventional regression joins leverages and residuals to produce a joint test of sensitivity termed $DFIT_i$. The change of fit associated with observation i is:

$$DFIT_i = \hat{y}_i \left[\text{predicted using } \underset{\sim}{\beta}(\text{all obs})\right] - \hat{y}_i \left[\text{predicted using } \underset{\sim}{\beta}(\text{all obs except i})\right]$$

which is calculated from

$$DFIT_i = h_{ii}\ (y_i-\hat{y}_i)/(1-h_{ii})$$

The normal regression hat matrix gives values of h_{ii}. Terms $(y_i-\hat{y}_i)$ are residuals.

The appropriate form of $DFIT_i$ for the poisson model involves the replacement of $(y_i-\hat{y}_i)$ by squared components χ_i, which is $(y_i-m_i)/\sqrt{m_i}$, to give:

$$DFIT_i = h_{ii}\chi_i^2 \ / \ (1-h_{ii})^2$$

Figure 3.7 draws out those points which depart significantly from the base-line of $DFIT_i$. Observation 21 has highest $DFIT_i$, standing at almost 2.4, largely as a result of being an outlier. Other households with high values record a combination of effects; for example, consumer 128 has an associated $DFIT_i$ equal to 2.2, this is ascribed to the joint effect of χ_i=7.8 and h_{ii}=0.034 - all are significant departures from the mass of values.

3.2 Choice Models

Example 2 Early Evening Shopping (Revisited)

In example 2 of this chapter a logit model was estimated for the relationship between revealed behaviour and socio-demographic variables. In particular, early evening shopping was expressed as a function of household size, employment and age. The goodness of fit was acceptable, but it was suggested that further attention be given to model sensitivity.

Many of the principles developed in conventional and poisson regression are applicable again, although some modifications are necessary. Assessment is made in two sections: firstly, extraordinary and influential observations are detected, and secondly the impact of these observations on estimated parameters and fitted values is measured. The discussion is informed by two earlier studies, firstly Wrigley and Dunn (1984a) and also Uncles (1984b).

3.2.1 Detection of Outlying and Unduly Influential Observations

The success of diagnostic tests depends largely on the identification of 'residual-like' values; these do not automatically 'drop out' of logit models but they can be extracted fairly easily. It is the disaggregation of global measures of fit that enables us to define 'components' of the model that are treated like residuals.

Two sources of diagnostic information are found: (a) measures of the discrepancy between observed and predicted probabilities (residuals), and (b) the amount of influence exerted by an individual in the space defined by observed veriables (leverages). The aim is to identify outlying residuals and influential leverages, and to see what effect these have on the credibility of our model.

(a) Outlying Residuals

Logit residuals are obtained from the disaggregation of two global goodness of fit statistics, namely chi-square and deviance. From Nelder and Wedderburn (1972, 375):

$$\chi^2 = \Sigma(y_i - p_i)^2 / p_i(1-p_i)$$

and

$$D = 2\left[\Sigma\, y_i \ln(y_i/p_i) + \Sigma(N-y_i) \ln \{(N-y_i)/(N-p_i)\}\right]$$

where y_i are observed responses and p_i are predicted probabilities of the logit model for $i = 1,2,...,N$ individuals.

Components χ_i and d_i are defined as:

$$\chi_i = (y_i - p_i) / \sqrt{p_i(1-p_i)}$$

and for $y_i=0$

$$d_i = \sqrt{-2 \ln(1-p_i)}$$

or for $y_i=1$

$$d_i = \sqrt{-2 \ln(p_i)}$$

These components measure the mis-match between observed and predicted probabilities, such that positive values indicate an under-prediction of choice probabilities and negative values are associated with over-predictions. Discrepant observations have high component values.

Scatter plots of χ_i and d_i versus household index values (figure 3.8) are standardised so that the value of single components can be evaluated against the t-distribution with N-K-1 degrees of freedom. At 95% significance the asymptotic threshold is almost ±2.0.

Some 22 χ_i components in figure 3.8(a) depart significantly from the mass of observations. Household 121, for instance, has a χ_i value in excess of 5.0 and a predicted probability of 0.04, this represents a large under-prediction of choosing to shop early in the evening. Usually large households do not engage in shopping during the early evening, for some reason household 121 behaves differently.

Components of deviance are more conservative. At 95% significance 12 of the χ_i values and 2 of the d_i values are significant outliers.

Residuals are ordered and plotted against standard normal deviates in figure 3.9, these graphs are analogous to the probability plots of conventional regression. Two features should be noted: (1) the overall form is S shaped with short tails, which is to be expected from an underlying sampling distribution that is logistic, and (2) outliers stand apart. Largest of the under-predictions are associated with households 121 and 98, while household 112 turns out to be an important negative outlier (given that no evening trip is recorded for this household in the diary data its predicted probability of 0.82 is a large over-prediction).

(b) Influential Leverages

Certain households may have undue weight in the model fitting process, in effect they 'bend' the regression line from its 'true' path. These households are said to possess high leverage in the space defined by observed variables. When leverages were derived for the poisson model we saw how the familiar hat matrix could be modified, and similar principles apply here.

For logit regression the projection matrix is determined from predicted probabilities p_i and the beta parameters are iterative re-weighted least-squares estimates. The covariate space is:

$$\underset{\sim}{p} = \underset{\sim}{V}^{\frac{1}{2}}\underset{\sim}{X}(\underset{\sim}{X}'\underset{\sim}{V}\underset{\sim}{X})^{-1}\underset{\sim}{X}'\underset{\sim}{V}^{\frac{1}{2}}\underset{\sim}{y}$$

where $\underset{\sim}{p}$ is a N * 1 vector of predicted probabilities
$\underset{\sim}{y}$ is a N * 1 vector of response values
$\underset{\sim}{X}$ is the N * K matrix of independent observed values
$\underset{\sim}{V}$ is the N * N matrix whose diagonal elements, v_{ii}, equal $p_i(1-p_i)$

and $(\underset{\sim}{X}'\underset{\sim}{V}\underset{\sim}{X})^{-1}\underset{\sim}{X}'\underset{\sim}{V}^{\frac{1}{2}}\underset{\sim}{y} = \beta$ which contains iterative re-weighted least-squares estimates

Knowledge of $\underset{\sim}{p}$ allows us to map the covariate space onto the vector of response values:

$$\underset{\sim}{p} = \underset{\sim}{H}\,\underset{\sim}{y}$$

where H is the modified hat matrix given by $\underset{\sim}{V}^{\frac{1}{2}}\underset{\sim}{X}(\underset{\sim}{X}'\underset{\sim}{V}\underset{\sim}{X})^{-1}\underset{\sim}{X}'\underset{\sim}{V}^{\frac{1}{2}}$. As a result, Pregibon (1981, 711) shows that the projection matrix is:

$$\underset{\sim}{M} = \underset{\sim}{I} - \underset{\sim}{H} = \underset{\sim}{I} - \underset{\sim}{V}^{\frac{1}{2}}\underset{\sim}{X}(\underset{\sim}{X}'\underset{\sim}{V}\underset{\sim}{X})^{-1}\underset{\sim}{X}'\underset{\sim}{V}^{\frac{1}{2}}$$

The diagonal elements of $\underset{\sim}{H}$, denoted h_{ii}, are leverages whose impact is greater when unity is approached. Belsley et al. (1980) recommend the threshold criteria of 2K/N and 3K/N.

Leverages from the logit model are shown in figure 3.10. Only three data points stand out - 124, 126 and 213 - these all lie above the recommended threshold criterion of 3K/N. All three points are associated with single-person households living off a low income. The full significance of these influences cannot be appraised until their impact on individual estimates is known, this is studied next.

Before concluding the study of outlying and unduly influential observations we offer a summary. A plot, using leverages and modified residuals as axes, expresses the joint effect. Drawn across figure 3.11 are contours corresponding to thresholds at 2*ave(h^*_{ii}) and 3*ave(h^*_{ii}). Three data points are high leverages and two points are outlying residuals - only three points exhibit large joint effects, so the diagnostics are exposing two essentially different features of the fit.

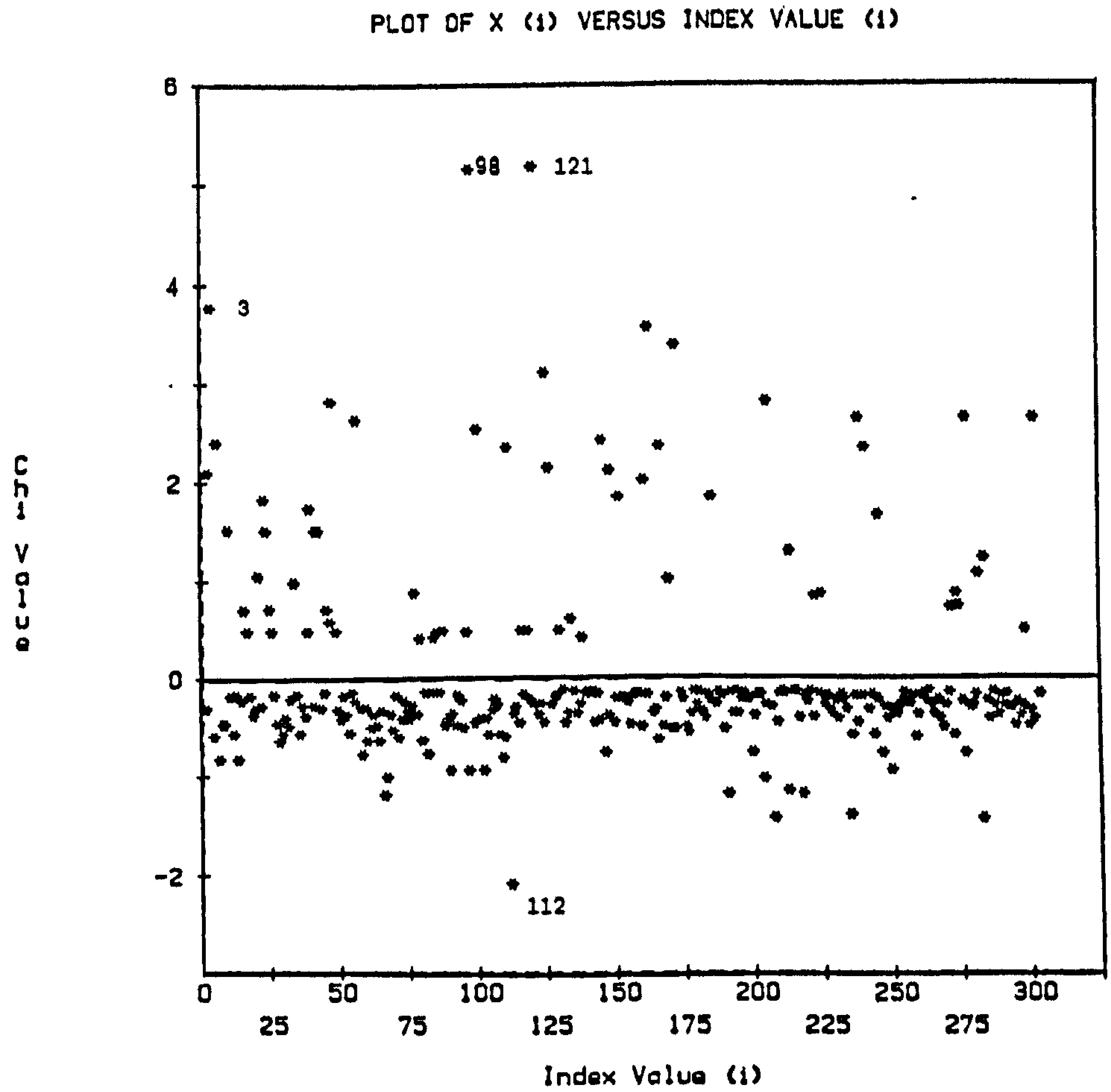


Figure 3.8 (a)

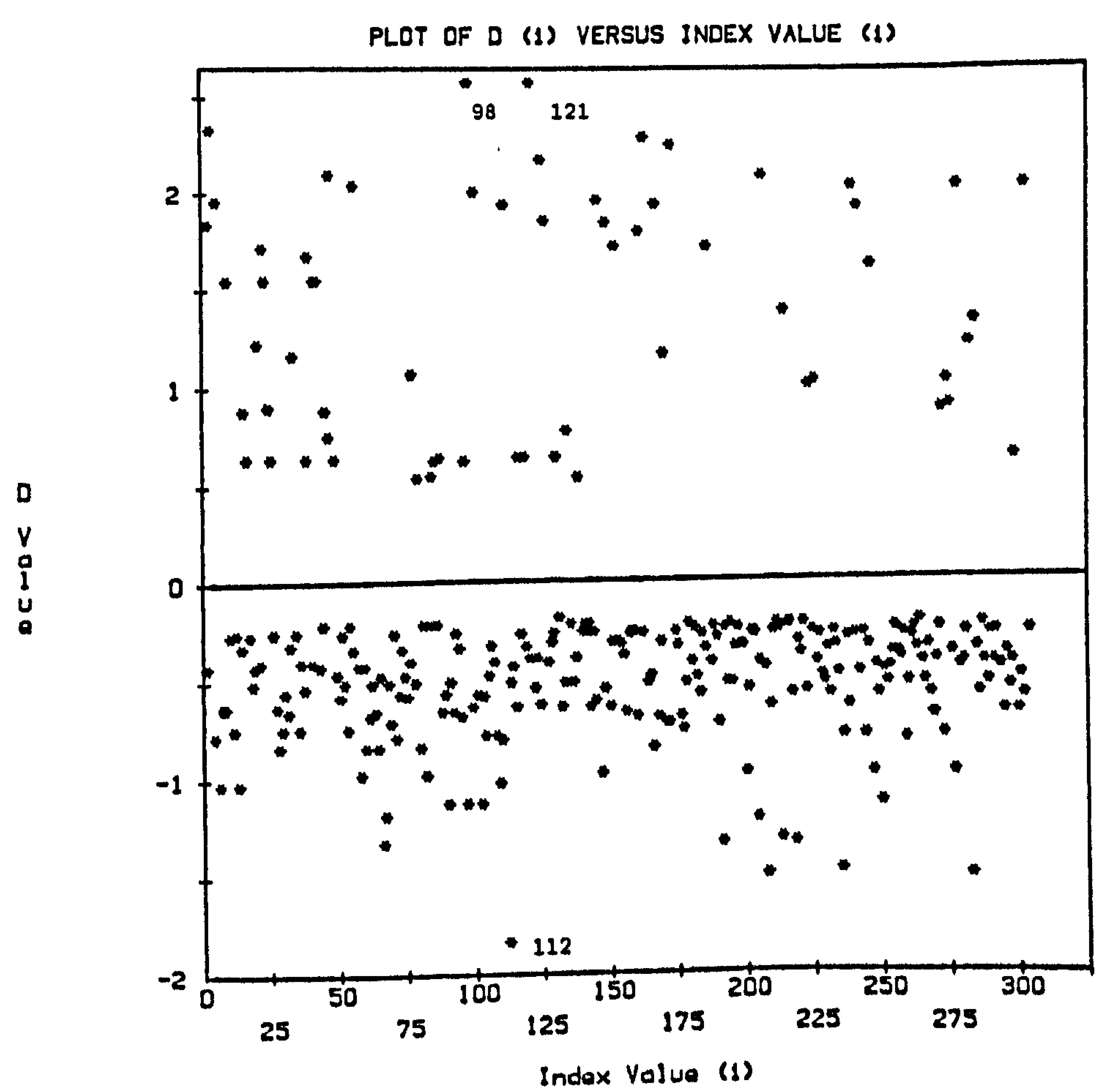


Figure 3.8 (b)

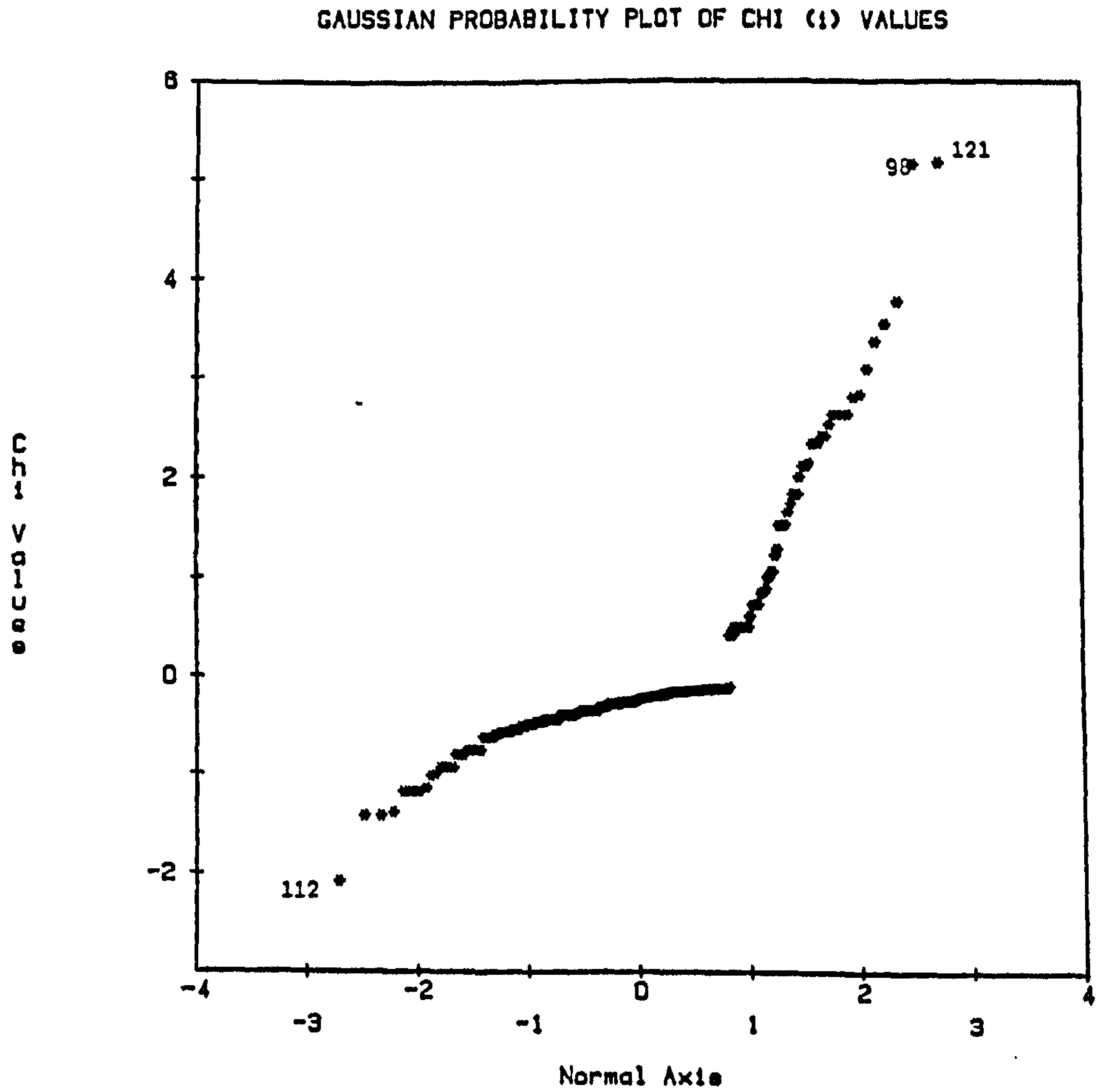


Figure 3.9 (a)

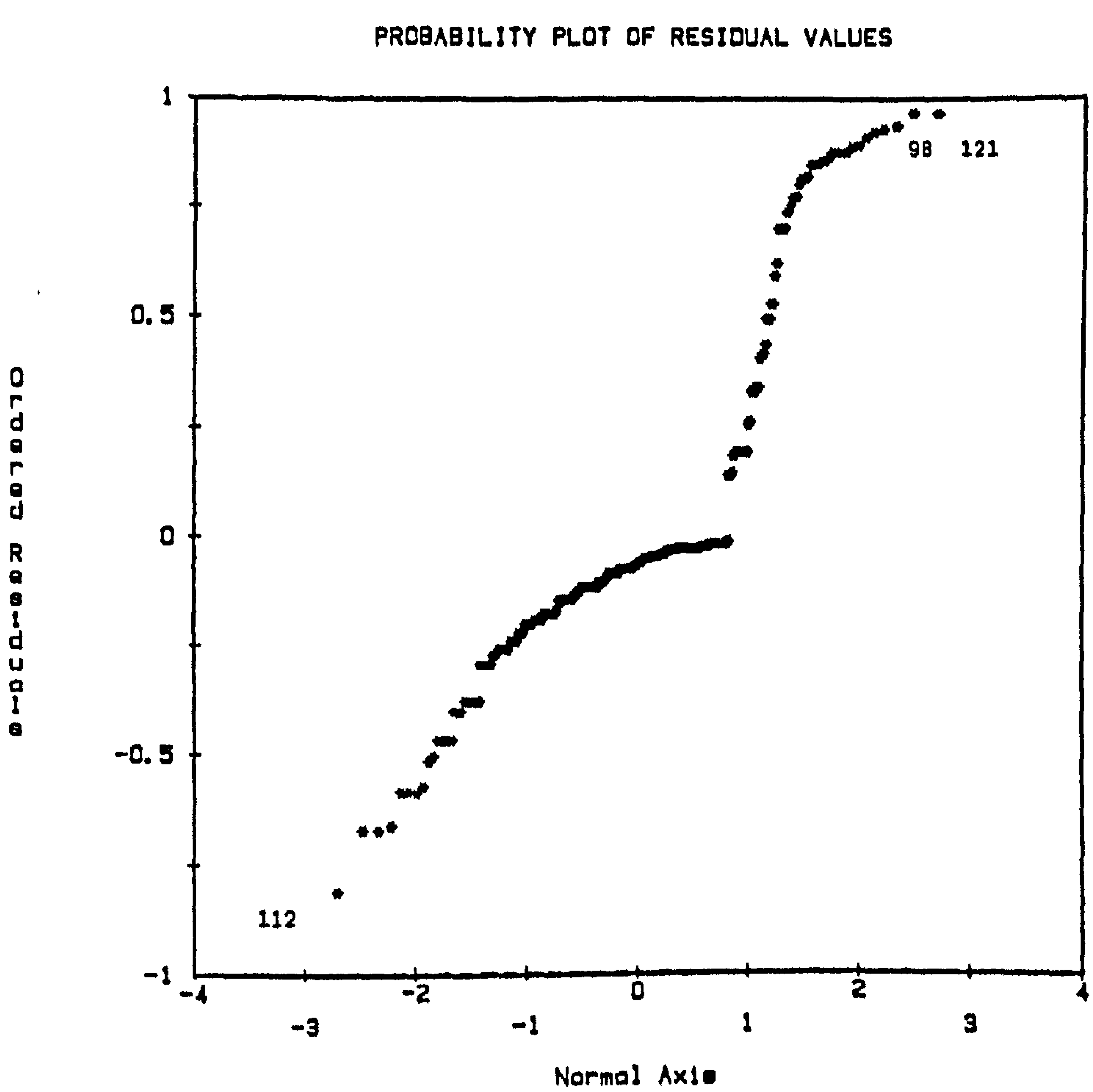


Figure 3.9 (b)

PLOT OF H (ii) VERSUS INDEX VALUE (i)

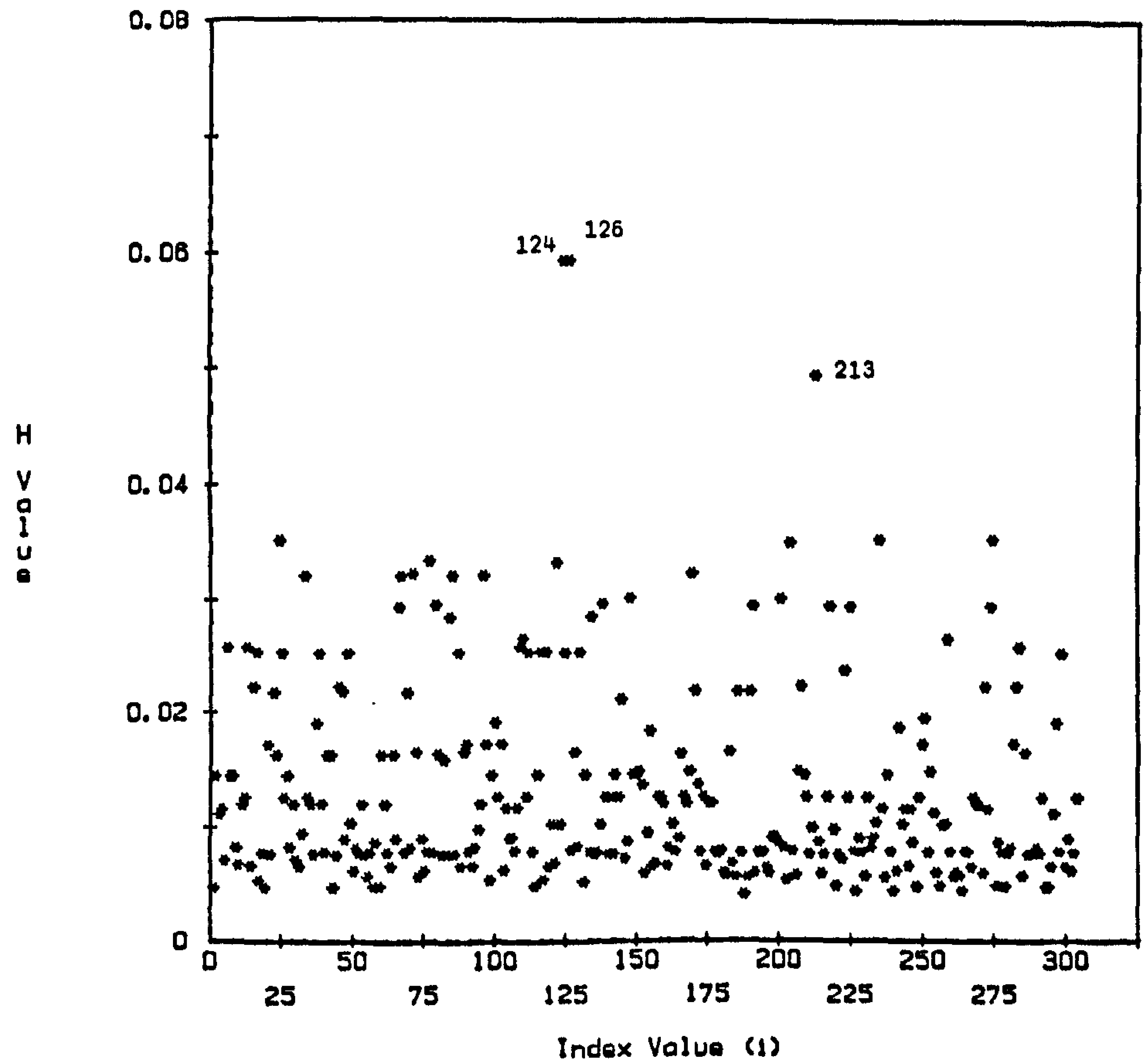


Figure 3.10

PLOT OF X (i) DIVIDED BY X VERSUS H (ii)

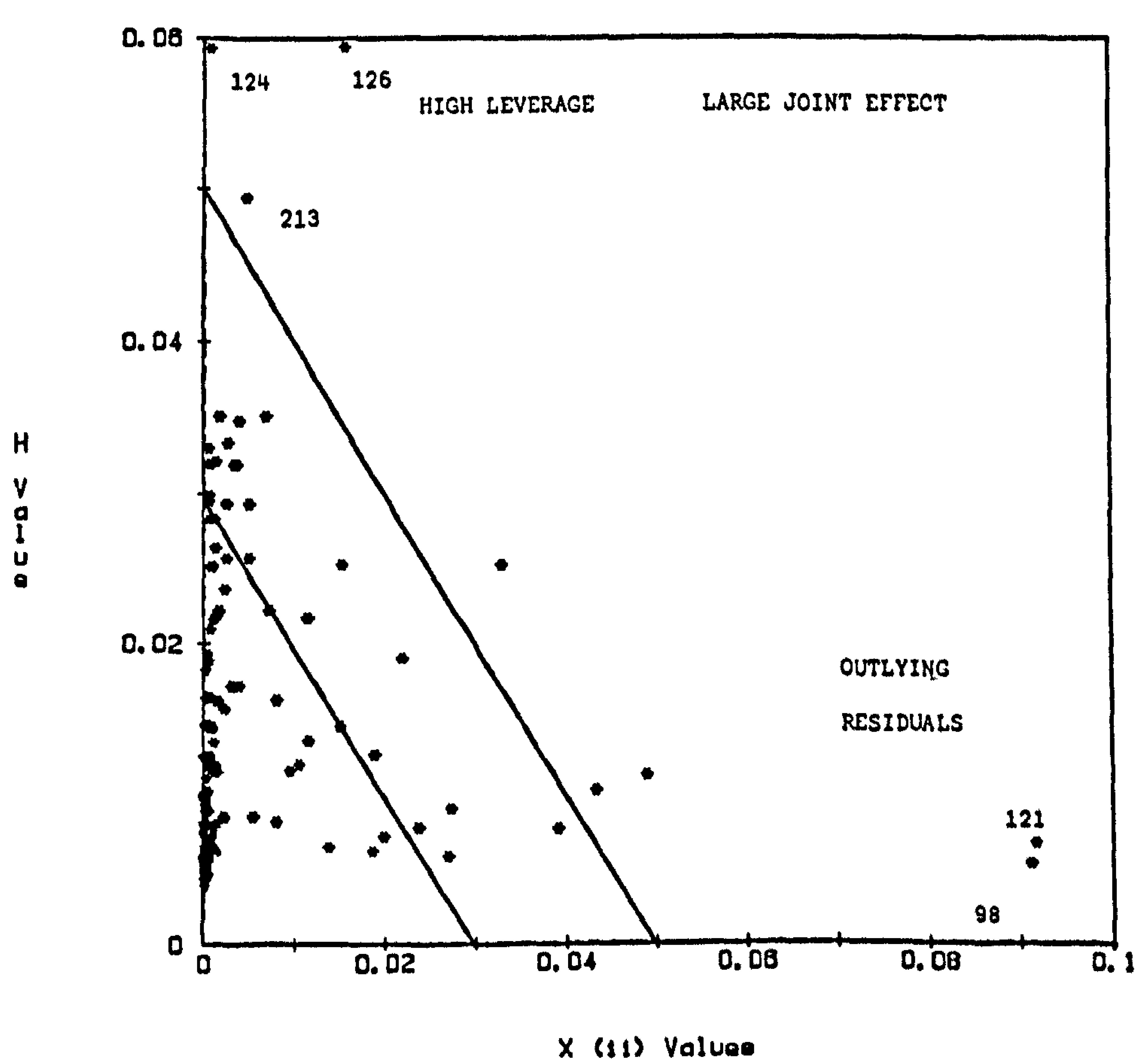


Figure 3.11

3.2.2 The Sensitivity of Model Parameters to Outlying and Unduly Influential Observations

A subset of observations have been identified as potentially having a large impact on model estimation. Now attention is turned to the influence of outlying and unduly influential observations upon estimated parameters and fitted values. To make these assessments the model is fitted when successive observations are deleted.

(a) The Sensitivity of Estimated Beta Parameters

The impact on estimated beta parameters is gauged from the successive deletion of $i = 1,2,...N$ observations. Deletion for a particular beta term, denoted $DBETA_{ik}$, is calculated from an approximate method that is equivalent to the poisson case. Standardisation is achieved by dividing through by the standard error, ie. $\sqrt{var(\beta_k)}$.

Plots of $DBETA_{ik}$ versus household index values are displayed in figure 3.12(a) to (c). Estimates for the household size variable (β_1 HHOD) are influenced by four individual data points which exceed 0.25 standard errors, but these counterbalance each other. In plot (b) several negative values are found, which suggests that the estimate of employment (β_2 EMPL) would rise if it were not for these anomalous data points. More stable is β_3 AGEG.

Listed in table 3.2 are the most important data points. $DBETA_{ik}$ values are shown in the middle columns and the major cause of instability is indicated in the final column. Most entries appear because they are outlying residuals, only 125 and 126 have strong leverage effects.

Taking the results as a whole, one point is clear: no value exceeds the threshold of 0.5 standard errors and therefore no single parameter estimate is over-sensitive to anomalous observations. Points of high leverage and outlying residuals - such as 3, 121, 125 and 126 in figure 3.12(a) - are not so influential that our confidence in parameter estimates is undermined.

(b) The Sensitivity of Fitted Values

Fitted values may be affected by wildcat observations in the design space. A measure is obtained for the discrepancy between fitted values when all observations are included and the fit when all observations except i are included. Components of χ^2 are used, where χ_i^2 equals the square of $(y_i-p_i)/\sqrt{p_i(1-p_i)}$ and the logit sensitivity measure is:

$$DFIT_i = h_{ii}\chi_i^2 / (1-h_{ii})^2$$

PLOT OF DBETA (i1) VERSUS INDEX VALUES

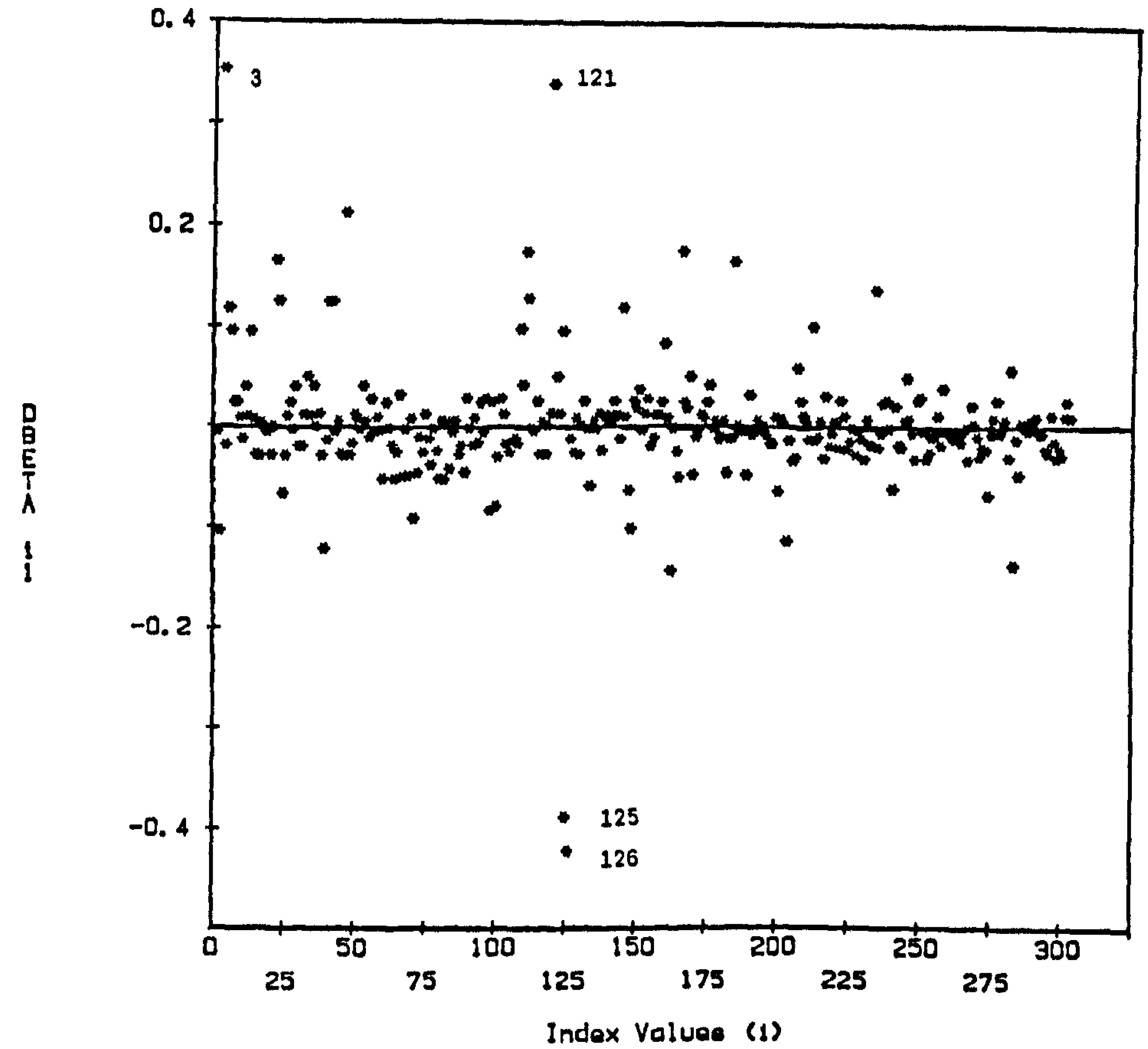


Figure 3.12 (a)

PLOT OF DBETA (i2) VERSUS INDEX VALUES

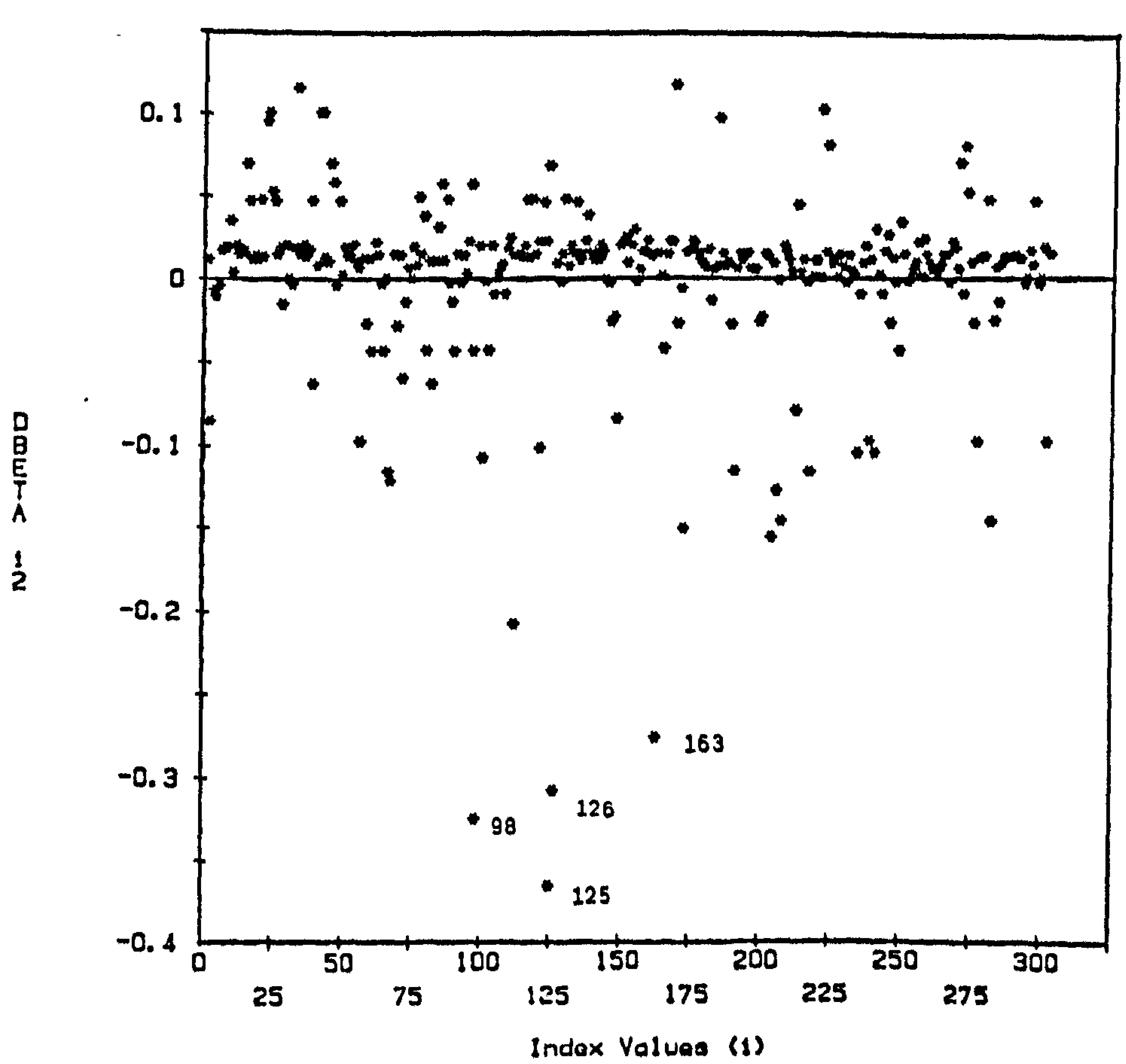


Figure 3.12 (b)

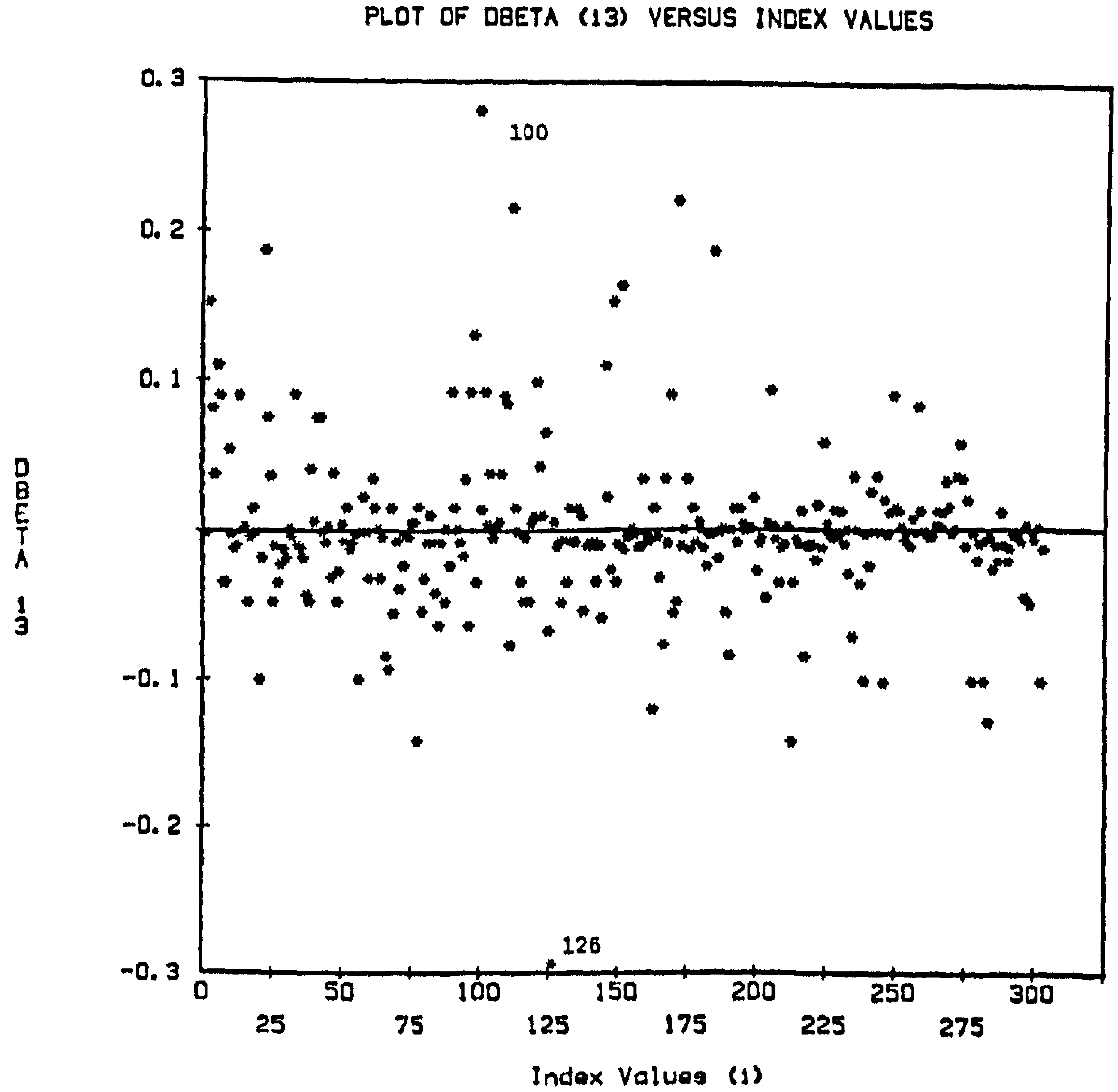


Figure 3.12 (c)

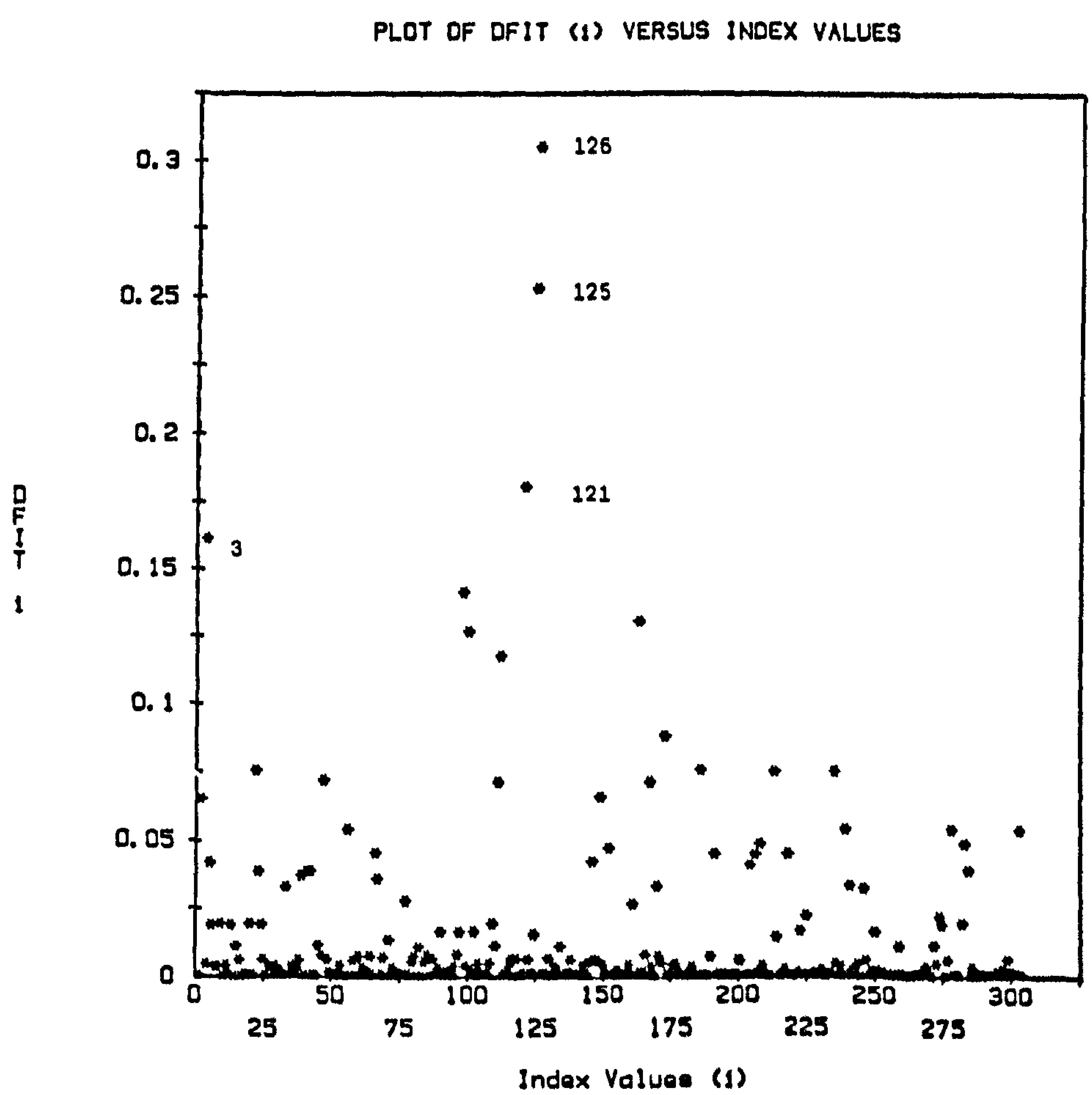


Figure 3.13

Table 3.2

Early Evening Shopping:
the Stability of Parameter Estimates

Household number	Values of $DBETA_{ik}$ HHOD	EMPL	AGEG	Cause of instability
3	0.35			R
98		-0.33		R
100			0.28	R
121	0.34			R
125	-0.39	-0.37		R & L
126	-0.42	-0.31	-0.29	R & L
163		-0.28		R

Only major effects are shown (ie. those where $DBETA_{ik} >$ ±0.25 of a standard error).
Negative signs indicate that the removal of household i would raise the value of β_k; positive signs indicate the converse.

L significant leverage, low residual
R significant residual, low leverage
R & L significant joint effect

Figure 3.13 plots $DFIT_i$ against households. Lying apart from other observations are 125 and 126, at 0.3 and 0.25 respectively. Recall that these are the only two households that exhibit high leverage, but neither their effect on $DBETA_{ik}$ nor on $DFIT_i$ is dramatic.

Analysis of all these diagnostic tests is encouraging. Residual-like measures can be defined and interpreted in a fashion that is familiar from conventional regression. Results show that outliers and influential points do exist, but the parameter estimates and fitted values are not destabilised; this gives us added confidence in our findings. Most data points are well-behaved and the final model is fairly reliable, however improvements can be made and these are illustrated in section 3.3.

3.3 Model Refinement

The poisson model of family maintenance and the logit model of early evening shopping are reconsidered. Overall, the poisson model is adequate and is reasonably insensitive to the wildcat behaviour of a few individuals. The exclusion of some data points might alter parameter estimates, but only marginally. Much more reliable is the logit model; the global goodness of fit statistic is significant and parameter estimates are fairly stable. However, there is always room for improvement and it is to model refinement that attention now turns.

Two refinements are considered, and then some caveats are discussed. (a) Observations may be anomalous for various reasons that are beyond the control of the researcher, in these circumstances the simplest option is to omit those points which do not conform. Alternatively, (b) a weighting procedure may be applied in order to dampen the influence of anomalous points. The second option gives estimates that are robust to atypical observations.

3.3.1 Removal of Outlying and Unduly Influential Observations

In many circumstances it is inadmissible to remove outlying and unduly influential observations. Such a form of re-estimation is legitimate, however, where the data point is known to be erroneous or where the need for stability is of overriding importance.

Household 21 exerts an abnormal and influential effect upon the poisson regression model, so this observation is removed and the model is re-estimated. Results are shown in table 3.3(a), the original values are included allowing comparisons to be drawn. All parameter estimates and t-statistics rise slightly. Reported deviance falls from 1771 to 1700, to give an improved likelihood

Table 3.3

Removal of Outlying and Unduly Influential Observations from the Poisson Model of Family Maintenance Activity and from the Logit Model of Early Evening Shopping

Model	Parameter Estimates				Likelihood Ratio
(a) Poisson	Constant	Children	Work status	Income	
Full model df 300	-0.31 (2.4)	0.21 (8.9)	-0.47 (6.6)	0.27 (11.9)	0.13
Remove 21 df 299	-0.47 (3.5)	0.22 (9.3)	-0.53 (7.4)	0.29 (12.9)	0.15
(b) Logit	Constant	Size	Percent employed	Age	
Full model df 300	-0.44 (0.5)	-0.32 (2.2)	0.04 (6.3)	-0.04 (2.8)	0.26
Remove 126 df 299	-0.95 (1.0)	-0.26 (1.7)	0.04 (6.4)	-0.03 (2.5)	0.26

Asymptotic t-statistics are shown in parentheses.
The full poisson model is outlined in section 2.1
The full logit model is outlined in section 2.2

ratio of 0.15. Our confidence in the model is greater and the results may have general applicability. But, this has been achieved at a cost; through the exclusion of household 21 we have (arbitrarily) discarded information about 18 combined shopping and family maintenance trips.

Household 126 exerts undue influence on the estimation of the logit model, and reported in table 3.3(b) are the results after this observation has been removed. Likelihood ratios are identical when rounded to two decimal places. If anything, removal gives us less confidence in the findings; estimated parameters for household size and age have lower absolute values and become marginally less significant, whilst the constant term rises. A t-statistic of 1.71 for household size is only significant at 90%, whereas in the full model a 95% level was accepted. The model may be less sensitive although in several respects it is less significant.

While it is possible to obtain model improvements through the deletion of outlying and unduly influential observations serious doubt must be cast on the propriety of such action. Erroneous data should be removed, but often extreme data points are measured correctly and are not erroneous. A preferable procedure is to downweight the influence of extreme data points.

3.3.2 Resistant Fits and Robust Estimation

As an alternative to the deletion of atypical observations, a number of resistant fitting procedures are attempted. Estimates that are less sensitive to outlying residuals or influential leverages are obtained by dampening the impact of extreme data points. 'We strive to make allowance for extreme observations' writes Pregibon (1982, 492) and he goes on to show how 'we seek a loss function which is less sensitive to outlying and/or influential data points than the loglikelihood function'.

To illustrate resistant fitting procedures the logit model of early evening shopping is re-estimated.

The maximum likelihood estimates are evaluated from:

$$\max = L(\underset{\sim}{x}'\underset{\sim}{\beta};\underset{\sim}{y}) = \sum_{i=1}^{N} l(\underset{\sim}{x}_i'\underset{\sim}{\beta};y_i)$$

where $x_i'\beta$ consists of a vector of parameter estimates β associated with variables x. Pregibon (1982, 493) shows that the maximisation of $L(\underset{\sim}{x}'\beta;y)$ is formally equivalent to the minimisation of deviance in a logit model

$$\min = D\{p(\underset{\sim}{x}'\underset{\sim}{\beta});\underset{\sim}{y}\} = \sum_{i=1}^{N} d\{p(\underset{\sim}{x}_i'\underset{\sim}{\beta});y_i\}$$

where $p(\underset{\sim}{x}_i'\underset{\sim}{\beta})$ is estimated from the logit function, and d{.} are squared components of deviance d_i^2 and are similar to those calculated previously in the discussion of logistic regression residuals. Arising from this association between minimum deviance and maximum likelihood are two resistant fitting procedures, one compensates for outlying residuals and the other compensates for influential leverages in covariate space.

(a) Resistance to Outlying Residuals (RST1)

A tapering function $\lambda(.)$ is applied to the squared components of deviance in an attempt to downweight outliers. The contribution of extreme residuals is tapered to give an expression for minimum deviance:

$$\min = D_\lambda\{p(\underset{\sim}{x}'\underset{\sim}{\beta});\underset{\sim}{y}\} = \sum_{i=1}^{N} \lambda\left[\, d\{p(\underset{\sim}{x}_i'\underset{\sim}{\beta});y_i\}\,\right]$$

Of several possible tapering functions Huber's loss function H is recommended. A value of $H=1.345^2$ serves as a critical threshold, residual values below H are not adjusted whereas those above H are given less weight:

$$\lambda(d_i) \begin{cases} d_i^2 & d_i^2 \leq H \\ 2(d_i^2\ H)^{\frac{1}{2}} - H & d_i^2 > H \end{cases}$$

It has been found from experience that a value of $H=1.345^2$ gives weighted estimates with roughly 95% asymptotic efficiency (see Pregibon 1982, also Wrigley and Dunn 1984a).

Original and weighted results (RST1) are placed together in table 3.4. Giving less weight to extreme residuals raises the goodness of fit statistic from 0.26 to 0.31 and there are marginal improvements in all t-statistics - all parameter estimates are significant at 99% and our results are more reliable. The absolute value of the parameter estimate associated with household size has risen slightly.

Since the weighted loss function is applied differentially across the sample, an index plot of weights is informative. Some 37 points are weighted by RST1, heaviest allowance is made for observation 121 which has a weight of 0.47 (figure 3.14(a)). Previously this 6-member household was shown to reveal wildcat forms of behaviour. Next to be dampened are observations 98, 3, 173 and 163, with weights in the range 0.47 to 0.53. Notice how the plot of weights versus household index values has automatically identified the outlying residuals that were shown by plots of components of deviance.

(b) Resistance to Influential Leverages (RST2)

A few points can exert undue influence on the fit because of their position in the covariate space, and a further modification of the minimum deviance procedure enables us to make allowance for this effect.

The loss function must now include the term $\pi(\underset{\sim}{x}_i)$ to give:

$$\min = \sum_{i=1}^{N} \pi(\underset{\sim}{x}_i)\ \lambda\left[d\{p(\underset{\sim}{x}_i'\underset{\sim}{\beta});y_i\} / \pi(\underset{\sim}{x}_i)\right]$$

The adjustment should have its greatest impact when leverages are large, otherwise the impact should be kept small. A value of $\pi(\underset{\sim}{x}_i)$ that has the desired effect is obtained from $\pi(\underset{\sim}{x}_i)=(1-h_{ii})/h_{ii}$ where h_{ii} is the leverage of observation i.

The fit from RST2 is altogether less interesting. Likelihood ratios do not alter, absolute values are virtually unchanged and only a fractional rise in t-statistics is seen (table 3.4 (c)). The vast majority of points receive unit weight, in fact only two points are affected by RST2 (see figure 3.14(b)). Household numbers 125 and 126, having weights of 0.89 and 0.66 respectively, are dampened a lot; it is recalled that these were the two points previously identified as having greatest influence on parameter estimates.

That only two points of leverage have an effect on the fit is encouraging, especially because most estimates remain invariant whether or not these points are deleted or weighted. The results from diagnostic tests and resistant fits give us added confidence in the findings from the logit model of early evening shopping.

Table 3.4

Resistant Fitting Methods for the Logit Model of Early Evening Shopping

Model	Parameter Estimates				Likelihood Ratio
	Constant	Household size	Percent employed	Age	
(a) Original Fit	-0.44 (0.5)	-0.32 (2.2)	0.04 (6.3)	-0.04 (2.8)	0.26
(b) RST1 Fit	-0.64 (0.7)	-0.39 (2.7)	0.04 (7.8)	-0.04 (3.6)	0.31
(c) RST2 Fit	-0.65 (0.8)	-0.30 (2.3)	0.04 (7.2)	-0.04 (3.1)	0.26

Asymptotic t-statistics are shown in parentheses.
Original fit is from section 2.2
RST1 and RST2 are weighted estimates which use the resistant fitting methods discussed in section 3.3.2

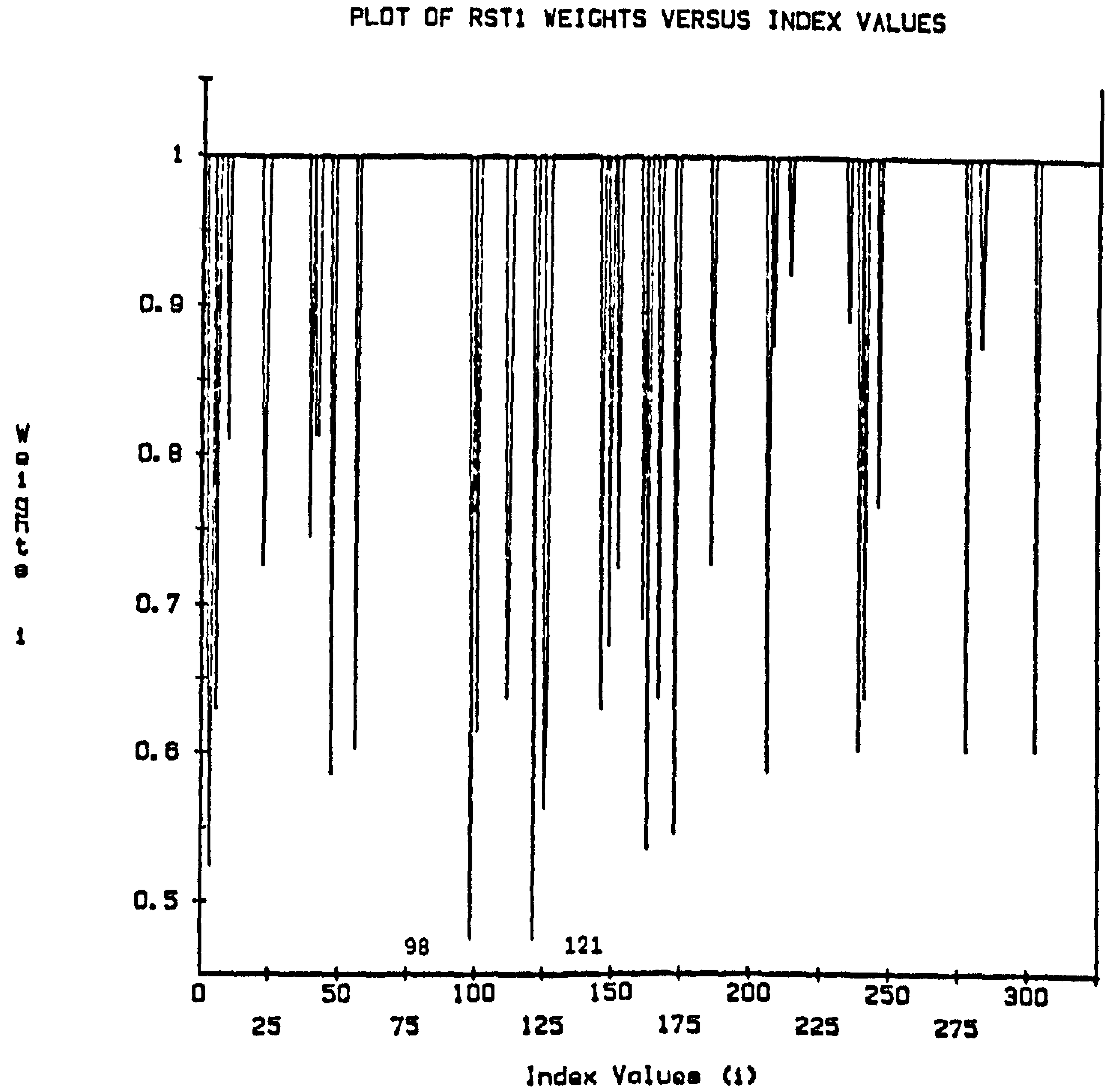


Figure 3.14 (a)

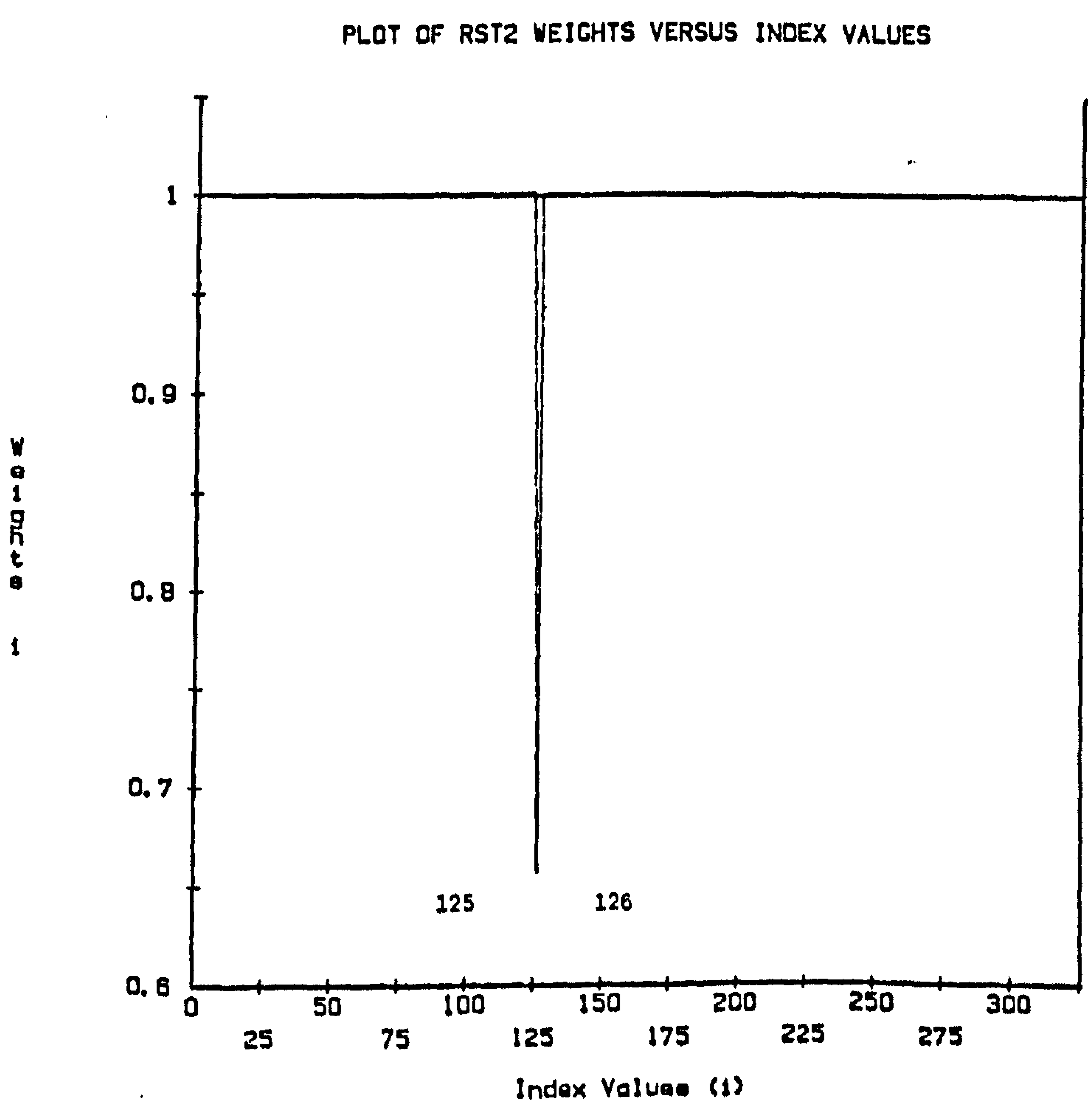


Figure 3.14 (b)

3.3.3 The Extraordinary and the Ordinary

Our evaluation of probability models has dealt with 'case' diagnostics and robust estimation. Such tests and checks are necessary when reliable findings are sought, yet they also affect the way we think about modelling. We need to be aware, for instance, of how attention is subtly shifted to the exceptional when the overall impression is of stability and conformity. It is only about 4% of the sample that behaves oddly, so 96% are perfectly unremarkable.

Diagnostics are best treated as early warnings. They draw attention to suspect estimates and/or suspect data, and it is for the analyst to decide whether it is the data or the model that is poor.

Poor data arises when observations are imprecise or missing. The fallibility of people's memories, for instance, can lead to mis-recording of events or inexact statements about what goods are bought and how much is spent. The problem (and ultimately the solution) lies with the design of samples and surveys, controls over data processing and coding, panel supervision and briefing. In chapter 1 it was shown how members of the Cardiff panel were carefully supervised and how coded tapes were checked for their consistency. No data set is error free but at least a high degree of quality control has been achieved.

Apart from improvements to the quality of data, another course of action is to refine the model itself. Already we have seen how extraordinary observations can be given less weight. Model refinements of this kind are most appropriate when there is no obvious or systematic reason for the existence of wildcat behaviour. The analyst has to accept the anomaly and make a statistical adjustment.

Alternatively there may be evidence of clustering: all members that are anomalous may live on the same housing estate or all may be very poor. Clustering implies that an important non-random effect has yet to be unravelled and that thought should be given to omitted variables and the inclusion of dummy variables. The decision to include additional variables is a pragmatic one, which depends on (1) the desired balance between generality and specificity, (2) whether there is multicollinearity between new and existing variables, and (3) the relevance of more variables in terms of policy and insight. Familiarity with the data, sharply defined objectives and common sense should help to get the balance right between parsimony and fine-tuning.

4 Discussion

Investigated in this final section are several ways in which incidence and choice models can be extended. This discussion serves to locate the modelling work in a broader context and provides an opportunity to comment upon a few unresolved issues. Many of these topics require further research, and some solutions are presented in the next chapter.

4.1 Extension of Incidence Models

Models of trip incidence predict the number of consumers who undertake r grocery trips within a limited period of time. Observed variables are included when the mean number of trips is estimated from a set of linear predictors. Through this process of estimation a link is established between observed exogenous variables and stochastic temporal components, and insight is gained into people's trip-making behaviour.

Now some thought is given to how dispersion in the sample might be incorporated within these models. Recall that in the purely stochastic negative binomial model the mean number of events is poisson for each consumer and these individual poisson distributions are allowed to vary through the sample. That is, the consumer's average rate of trip-making is poisson in the long run, and this long run average varies from person to person, to describe a gamma distribution in the whole sample.

For a single time period the theoretical proportion of the sample who undertake r trips is:

$$p_r = \frac{\Gamma(r+k)}{\Gamma(r+1)\ \Gamma(k)} \left(\frac{m + k}{k}\right)^{-k} \left(\frac{m}{m + k}\right)^{r}$$

where m is the long run average rate of occurrence and k is the negative binomial exponent or 'shape' parameter.

Let the averages associated with $i = 1,2, \ldots, N$ consumers vary as a log function of linear predictors, then:

$$\ln\ (m_i) = \underset{\sim}{x}_i'\underset{\sim}{\beta}$$

If m in the negative binomial equation is replaced by the exponent of linear predictors then a regression-type model is derived. Effectively the probability of r trips is a function of observables (through the mean) and random components (poisson error components).

The idea that socio-demographic, spatial and attitudinal variables can be incorporated into negative binomial models is easy to appreciate. Less easy to achieve is empirical estimation. Maximum likelihood methods have to be used for the estimation of parameters, and generally this necessitates some form of numerical optimisation.

Maximum likelihood estimation enables predictions of consumer behaviour to be disaggregated. For instance, if accessibility is believed to affect choice of store, then those consumers who have good access will reveal high rates of patronage and more repeated patronage. Theoretical values for these aspects of behaviour can be calculated from the negative binomial regression model (see Wrigley and Dunn 1985 for examples).

Theoretical introductions to this work are provided by Broom (1982) and Broom and Wrigley (1983). Beyond the geographical literature an important statement is that of Hausman et al. (1984). Records have been kept of US companies who apply for patents, and Hausman and his colleagues use these panel records to build a model of applications for patents that depends on R & D spending, random temporal components and dispersion effects.

Ostensibly negative binomial regression appears to be a good way to structure information that is disaggregate and longitudinal. But, for several reasons, it is less appealing than first expected:

(1) Computation is complex and some numerical trials have shown that the procedure can be unreliable.

(2) The sum of negative binomial distributions is not another negative binomial distribution; Wrigley and Dunn (1985) refer to this problem as an 'aggregation problem'. While the aggregation problem may not be severe it certainly represents an outcome that is statistically inelegant.

(3) The negative binomial distribution is generated from an exceptionally wide range of underlying processes. Where the objective is to describe data the need to specify a distribution that is 'behaviourally correct' is less pressing, yet the problem remains mildly disturbing.

(4) Overriding all these considerations is the fact that a more general and reliable model is available that subsumes negative binomial regression and logit regression as special cases.

Rather than probe deeper into negative binomial regression an integrated approach is developed in the next chapter.

4.2 Extension of Choice Models

So far the use of logit models for temporal studies has not advanced beyond comparative statics (such as the daily cross-sections presented in example 4). It would be desirable to have a more direct way to measure temporal components. A second outstanding issue refers to the arrangement of choices. Each consumer faces a multiple set of choices and these might be presented to the individual as a nested sequence of decisions. Thus, fundamental choices are made at an early stage, and other choices are only pertinent once an earlier decision has been resolved. Both these issues - temporal components and nested components - are discussed in the following sections.

(a) Temporal Components in Models of Choice

A theoretical statement by Tardiff (1980) hints at what is possible. Temporal components enter Tardiff's logit model in three ways: through time-varying parameters, through dummy variables that capture the effect of choices made in the previous period, and through random components that vary between individuals and time periods. If the observation period is fairly lengthy the dummy variable can be replaced by a lag operator, and this enables feedback and temporal dependence to be studied.

Other approaches have looked at probit models. The standard probit model of choice can handle complex covariance structures between error terms, and this fact is exploited in order to isolate temporal components. Effectively, accumulated experience and inertia are isolated from random 'taste' variations within the sample covariance matrix.

Empirical studies based on the probit model have tended to rely upon data collected over two periods, and normally these data have been obtained before and after a policy change. Some examples are given by Daganzo and Sheffi (1982) and Johnson and Hensher (1982). Tentative results show that temporal components do have a significant impact on: (i) parameter estimates, (ii) log-likelihood functions, and (iii) policy responses (elasticities). For instance, where accumulated experience is strong the choice probabilities are less responsive to changes in travel cost or changes in travel time.

These statements are an important advance over the somewhat dimensionless and timeless logit and probit models of the past. At present, those extensions which build upon the logit model have operational and estimation advantages over probit, indeed probit becomes inefficient and cumbersome when the number of choices or the number of time-periods exceeds two.

(b) Nested Components in Models of Choice

In this section the arrangement of multiple choices is considered. Recall that the probability of a choice is estimated from:

$$p_i = e^{\underset{\sim}{x}_i'\underset{\sim}{\beta}} / (1 - e^{\underset{\sim}{x}_i'\underset{\sim}{\beta}})$$

For cases where there are R unordered alternatives, the binary logit model is generalised to a multinomial expression. The choice probability of selecting alternative r over g, where $r \neq g$, is:

$$p_{ir} = e^{\underset{\sim}{x}_{ri}'\underset{\sim}{\beta}} / \sum_{g=1}^{K} e^{\underset{\sim}{x}_{gi}'\underset{\sim}{\beta}}$$

Routine estimation of multinomial models is possible using a package such as BLOGIT (Crittle and Johnson 1980).

All the basic derivations of multinomial logit assume that the odds of choosing alternative r over g does not depend on whether other alternatives are available (ie. the introduction of another alternative k would draw its share equally from r and g). This property of independence for irrelevant alternatives is an axiomatic assertion. In practice the random components may be correlated and failure to recognise this leads to counterintuitive results (cf. red bus / blue bus problem, see Wrigley 1985). One solution to the dilemma is to impose a structure on the estimation process.

Let the decision process be two-staged. The major decision is whether or not to make a trip (t=0,1) and the subsidiary choice is which district centre to visit (r=1,2,...,R). Estimates of the subsidiary choice are brought together to define an 'inclusive value';

$$IV = \ln \{ \sum_{r=1}^{R} e^{\underset{\sim}{x}_{ri}'\underset{\sim}{\beta}} \}$$

where $\underset{\sim}{x}_{ri}'\underset{\sim}{\beta}$ are linear predictors that refer to choice of district centre.

So, the probability of choosing a district centre, conditional on there being a trip, is:

$$p_i(r \mid t=1) = e^{\underset{\sim}{x}_{ri}'\underset{\sim}{\beta}} / e^{IV}$$

and the probability of a trip occurring in the first instance is:

$$p_i(t=1) = e^{\underset{\sim}{z}_i'\underset{\sim}{\alpha} + IV} / (1 + e^{\underset{\sim}{z}_i'\underset{\sim}{\alpha} + IV})$$

where $\underset{\sim}{z}_i'\underset{\sim}{\alpha}$ are linear predictors for trip incidence.

This sequence of steps is developed by Broom (1982) and shares an affinity with the nested logit model proposed by Sobel (1980). Many decisions in real life exhibit a natural nested, hierarchical or sequential order. In residential choice, for instance, the primary decision is whether to own or rent, within the rented sector there is 'choice' between local authority housing and private rented accommodation, and so on (Longley 1982).

More relevant to our discussion is the way transport and shopping decisions are hierarchical: the decision to make a trip is followed by choice of mode-to-get-there and choice of destination. Ideas about nested decision-making may be rooted in behavioural theory (Uncles 1982), but the empirical attraction of these models is their tractability, computational efficiency and avoidance of the independence from irrelevant alternatives axiom.

4.3 Model Specification

A partial approach has been adopted in this chapter: we have concentrated upon the derivation and application of a few probability models, evaluated the estimates obtained from these models, and suggested some extensions. This stance is preferable to a superficial review of all the techniques that one might consider. There remain, however, at least three outstanding problems: functional form, model comparison, and specification errors.

Easiest to resolve is the question of selecting the most appropriate functional form. All estimates have been calculated from additive linear predictors; it is feasible, argue many researchers, that an improved fit can be obtained from alternative functional forms. Most common are the Box-Cox and Box-Tukey transformations. For logit models, transformations are available through the use of GLIM macros or from the BLOGIT package (see Hensher and Johnson 1980, 186-91). Trials using data from Cardiff have not led to any worthwhile improvements in parameter estimates or log-likelihoods, and the extra computation is not justified. Only where choice elasticities are calculated do results show some variation.

A related issue is that of model comparison and selection. The models presented in this chapter have been selected on grounds of likelihood ratios, the significance and stability of parameter estimates, and overall robustness. An alternative approach is illustrated by Halperin et al. (1984) and Longley (1984) who use a matrix comparison test to select a suitable logit model. An empirical matrix of predicted probabilities is assessed against a randomly generated reference distribution, and the most significant departure is accepted as the best model.

More fundamental is the attention that needs to be given to specification errors: omitted variables, heteroscedasticity, multicollinearity, and other systematic trends and dependencies among residuals. Horowitz (1980) has started to address these problems and econometric analyses of panel data are beginning to tie together many of these concerns.

In the next chapter an attempt is made to bring together incidence and choice models, to look at temporal effects, and to find a broader definition of choice sets using our knowledge of activity bundles. Such an integration raises many questions about model specification. Some of these issues are treated explicitly, such as the analysis of residuals and the detection of omitted variables. As in this chapter, the approach is selective and designed to focus on those aspects of model specification that are particularly relevant for the analysis of panel data.

CHAPTER 5

INTEGRATED MODELS OF CONSUMER ACTIVITY

Economists set themselves too easy, too useless a task if in tempestuous seasons they can only tell us that when the storm is long past the ocean is flat again.

John Maynard Keynes (1923)
'A Tract on Monetary Reform'

1 Introduction

The purpose of this chapter is to integrate many of the ideas set forth in earlier sections. We have seen that bundles of activity can be defined quite economically, and that similar bundles will recur through time. We have considered how discrete choices and the incidence of events can be modelled from a set of related stochastic models. Now stochastic and descriptive models are brought together.

Links are forged between two modelling traditions: stochastic models formed in statistics and marketing are integrated with descriptive models developed in econometrics and mathematical demography. Matching these traditions is not a smooth exercise; disciplines have different aims and objectives. Some disciplines emphasise the need for practical implementation (models must be tractable, efficient and transparent), for others abstract integrity is of greater concern (models must be coherent, elegant and stable). Such objectives are not necessarily incompatible. Given technological innovation, the infeasible ideas of today may become tractable tomorrow. Powerful computers and numerical analysis, in particular, mean that it is possible to think about integrated approaches.

This chapter shows how panel data are used to represent a series of individual choices from a finite set of choice alternatives. Throughout, the series of outcomes depends both on unobservables and on measurable aspects of behaviour and life-style.

Three elements are central to the specification of such a model: intertemporal dependence, heterogeneity and non-stationarity. First these concepts are defined. Next to be discussed is an intuitive appreciation of what is meant by state dependence and heterogeneity. A model which explicitly measures variability is introduced. Initially some simple probability theory and hand calculations are worked through, but the bulk of this chapter is devoted to applications. Applications refer to the repeated choice of travel mode and repeated occupancy of activity bundles. Finally some thought is given to how complex models might give rise to empirical and theoretical generalisations and where extensions might be expected in the near future.

1.1 Definitions

Literature about panel data is to be found in all manner of subjects, from biostatistics to econometrics. As a result technical terms are confused and duplicated, so some clarification is needed at the start. Essentially there are three groups of related effects: intertemporal dependence, heterogeneity and non-stationarity. Each of these is defined in turn.

1.1.1 Intertemporal Dependence

Intertemporal dependence is the conditional relationship between future and past experience. Typically, individual consumers who made a choice in the past are more likely to repeat the same choice in the future than are consumers who have not had such an experience. It is plausible, for instance, that buying at one grocery outlet will prompt a re-evaluation of utility functions. The consumer might upgrade the positive attractions of the store, and in this case future choices will be shaped by past experiences.

In noting the existence of intertemporal dependence it is important to distinguish between state dependence that is 'true' and that which is 'apparent'.

(a) True state dependence

This refers to the influence of past experience on future choices; such an influence arises because of real barriers to change. There is a genuine behavioural effect - past utilities, commitments, investments or motives make the choice of one alternative much more probable. True state dependence is also called structural dependence, feedback, cumulative inertia and true contagion.

(b) Apparent state dependence

This arises when individuals differ in their propensity to experience an event or to select a choice. Where these differences among a sample are correlated over time, previous experience will appear to determine future choices. Apparent state dependence is not an outcome of intertemporal dependence, rather it is an indicator of unobservables which persist through time. The effect is also termed spurious state dependence.

1.1.2 Heterogeneity

Heterogeneity is the variation in a sample due to observed differences and to serial correlation in unobserved exogenous influences. The two forms of heterogeneity are quite distinct.

(a) Sample variance

Sample variance describes the range of values which observed exogenous variables take across a panel. The researcher may have, for example, information about disposable family income and personal mobility; both these influences on choice probabilities will vary across a sample in a measurable manner.

(b) Omitted variables

Persistent serial correlation mainly arises from the influence of unobserved exogenous variables. These are omitted variables. Omitted variables are likely to be associated with personal motivations and tastes, and with unmeasured socio-economic characteristics. It is important to note that the influence of omitted variables and apparent state dependence are related phenomena.

1.1.3 Non-Stationarity

Non-stationarity is the variation over time of individual event probabilities owing to external factors. External factors include seasonality, structural change, macro-economic fortunes, and institutional reform. Commonly non-stationarity is represented by time-varying parameters. The specific form of these parameters depends on whether the event is an incidence or a choice.

(a) Incidence

Time-varying rates of shopping provide an example of how incidence might be non-stationary. For instance, the secular rise in levels of car ownership and in deep freezer ownership means that shopping is becoming less frequent.

(b) Choice

Time-varying propensities to choose a certain type of shop illustrate how choice might be non-stationary. Greater awareness of healthy living and dietary planning, for instance, may mean that the propensity to shop at delicatessen and health shops increases relative to convenience and discount stores.

Most changes to the external environment affect major life-cycle decisions - migration, residential choice, access to labour markets - but will have little impact on regular store patronage or frequent choice of travel mode. Thus, most aspects of short-term consumer and travel behaviour are time invariant.

Failure to separate these effects can seriously mislead researchers. That the problem is non-trivial is shown by the following example of store choice. A discrete choice model is proposed in which shoppers choose to visit the food-hall of a department store, or alternatively choose to patronise a suburban supermarket. The observed sequence of choices suggests that future decisions will be conditional on previous experience; in fact many more shoppers choose to shop regularly at the supermarket.

From such evidence a number of models might be proposed in order to characterise intertemporal dependence. One option is the first-order Markov model (or last purchase loyal model) which allows choices in the last period (only) to determine current choices. The entire history of patronage influences choice when a Pólya process is postulated. Alternatively, continuous choice of the supermarket might suggest a renewal process. Perhaps the most likely higher-order model to characterise the choice sequence is the learning process and there are some studies to support this view (Aaker and Jones 1971, Burnett 1977).

But intertemporal dependence may be fictitious - apparent not real - arising because of persistent serial correlation. Persistent serial correlation, recall, is due to unobserved variation. Unobserved variation is not difficult to find in the store-choice example: a variable to capture the influence of proximity to the supermarket might have been omitted. The true effect, therefore, might be that the sample is heterogeneous. Some shoppers are proximate to the supermarket and will be prone to shop there (irrespective of their relative evaluation of facilities elsewhere, and irrespective of knowledge acquired about stores, and irrespective of where they choose to shop on other occasions), other shoppers are distant from the supermarket and will tend not to shop there.

Failure to allow for important variables (like proximity), or for random variation in tastes, often encourages researchers to propose higher-order models when the true process is zero-order or Bernoulli. Under these circumstances intertemporal dependence is said to be 'apparent' or 'spurious'. In an analysis of store-choice models Crouchley et al. (1982) explicitly remarked upon 'the need for properly controlled tests of more parsimonious models'. Concluding their analysis of store-choice Crouchley et al. (1982) found that the Bernoulli model - where choice probabilities are memoryless - performed better than more complex linear learning models.

It is possible to refine the definitions. Account can be taken of ordered and unordered choice sets, initial conditions and truncation, and right and left censoring. However, several of these issues arise from imperfect data. Statistical fudging ought not to be a substitute for direct attention to panel attrition, incomplete sampling, sample bias and conditioning (see Chapter 1, section 3). The payoff between survey design and statistical analysis is an important area for future research; an area that is not developed here. Instead, subsequent sections investigate intertemporal dependence and heterogeneity in detail and only in the discussion of generalised models are some of the broader themes raised again.

1.2 Model Integration

Spurious statistical effects (such as apparent state dependence) have been recognised since the early biomedical work of Feller (1943) and Bates and Neyman (1952). These biomedical researchers showed that 'spurious contagion' can arise when some members of a sample are more accident prone than others. Elsewhere the statistical effects found in biomedical work have been translated in order to investigate problems in marketing and behavioural analysis (Frank 1962, Massy et al. 1970). Now, with the widespread availability and use of longitudinal micro-behavioural data, greater awareness of these effects is needed.

This section starts by offering an intuitive feel for intertemporal dependence and heterogeneity. Then a formal model of longitudinal choice is presented.

Consider two travel choice situations. In both schemes a superstore on the edge of Cardiff can be reached by car C or by bus B.

People are split evenly into two groups for the first scheme. There are 150 type I consumers, for whom there is a 0.8 probability of car travel on any given occasion. Type II consumers also number 150 and have a 0.8 probability of choosing to travel by car. In total there are 300 people. Choice probabilities are assumed to be constant and independent of choice histories.

The joint probability of travel by car under scheme one is:

$$\begin{aligned} p(C) &= p(C|I)p(I) + p(C|II)p(II) \\ &= 0.8*(150/300) + 0.8*(150/300) \\ &= 0.8 \end{aligned}$$

Another shopping trip is made and the conditional probability that the car is favoured on both occasions is:

$$\begin{aligned} p(CC|C) &= [p(CC|I)p(I) + p(CC|II)p(II)] \;/\; p(C) \\ &= [(0.8*0.8)*(150/300)+(0.8*0.8)*(150/300)] \;/\; 0.8 \\ &= 0.8 \end{aligned}$$

Therefore, the joint probability of choosing to travel by car remains constant in the homogeneous sample. This scheme corresponds to the zero-order or Bernoulli model of independent trials, where each trial is equivalent to a decision.

The second scheme illustrates how spurious state dependence can arise from heterogeneity. Consumers who patronise the superstore are of two different types: 100 have a high propensity to travel by car and 200 have a high propensity to travel by bus. Choice propensities differ because of wealth, infirmity, predilection and so on (the specific reason is of little consequence). The 100 type I consumers have a 0.8 probability of car travel. A 0.08 probability of car travel characterises type II consumers.

Among these 300 people the joint probability of choosing to go by car is:

$$p(C) = p(C|I)p(I) + p(C|II)p(II)$$
$$= 0.8*(100/300) + 0.08*(200/300)$$
$$= 0.32$$

The conditional probability that another trip is made by car becomes:

$$p(CC|C) = [p(CC|I)p(I) + p(CC|II)p(II)] / p(C)$$
$$= [(0.8*0.8)*(100/300)+(0.08*0.08)*(200/300)]/0.32$$
$$= 0.68$$

Car travel on the first trip 'appears' to double the probability that the second trip is by car.

Ostensibly the simple Bernoulli model cannot be sustained and a higher-order process must be assumed. Several justifications for a higher-order model are to hand; for example, 'there is cumulative inertia' or 'consumers are last-mode-loyal'. Yet the 'true' probabilities have not changed, they remain 0.8 and 0.08 for type I and type II consumers respectively. The apparent rise in the joint propensity to travel by car over successive trips arises because of heterogeneity in the sample. Invocation of higher-order processes is misplaced in these circumstances.

If only cross-sectional data are available it is not possible to distinguish between the effects of heterogeneity and state dependence, and we have to be content with measures of location (mean or mode). Panel data are far more versatile and enable us to investigate higher moments (ie. the amount of variability in data is assessed and spurious effects are separated from true processes). The building blocks for this are presented next.

Reconsider the situation where a consumer can choose between car or bus. Predicted outcomes are expressed as a function of measured variables, such as the socio-economic attributes of shoppers and perhaps time-varying influences owing to special discounts or promotions. Such observed variables partly account for heterogeneity, state dependence and non-stationarity. Not all influences, however, are known to the researcher: motivations and tastes may be unobservable and socio-economic data may be poor in quality (ie. many potential variables are omitted). These omitted variables are collected within an individual-specific error term. For an individual:

$$\text{choice probability} = f\ (\text{observables}) + \text{error term}$$

Since the behaviour of specific individuals is not of interest, choice probabilities are aggregated. The mean probability of choosing to travel by car is a function of observed variables (whose values differ across individuals) and the distribution of error terms (more correctly, the joint density function of of individual-specific error terms).

Across the sample of travellers there is a 'mixture' of individual choice probabilities and these can be described by a statistical distribution. All examples presented here assume that the mixing distribution is parametric, although arbitrary non-parametric forms are mentioned in section 4.2. For a sample:

$$\text{distribution of choice probabilities} = f\,(\text{observables}) + \text{distribution of error terms}$$

By way of example we shall consider a binomial choice process and a mixing distribution of the 'beta' type. On each choice occasion the shopper chooses to travel by car or by another mode, and it is convenient to assume that the number of occasions is finite (to give r car choices out of n trips). Let p be the proportion of car trips and q=(1-p) be the proportion of all other trips (bus, walk, etc). Then, for an individual, a simple binomial formula is derived:

$$p_r = \binom{n}{r} p^r q^{n-r}$$

for $r=0,1,\ldots$ and $0<p_r<1$.

The probability p of car travel is constant and independent of previous choices (ie. the process is Bernoulli).

Next, we note that the value of p is likely to vary from consumer to consumer because of socio-economic, attitudinal and taste differences. Let all these possible influences be collected into a composite error term for each individual. Now assume that the error terms are distributed across the sample. Without justification at this stage, a beta distribution is assumed (ie. across a sample the 'mixture' of individual probabilities and individual error terms describes a beta distribution).

Then the proportion of shoppers who select car travel r out of n trips is given by the beta-binomial expression:

$$p_r = \binom{n}{r} \frac{B(a+r,b+n-r)}{B(a,b)}$$

for $r=0,1,\ldots$ and $0<p_r<1$ and $a,b>0$; and where $B(a,b)$ is the beta function with parameters a and b.

There are three parameters in the model. The number of trips n is pre-specified. Often the two additional parameters a and b are derived empirically (see example below). But, given further information, numerical estimates can be obtained. When probabilities are disaggregated for individuals, or individual types, numerical estimates provide a lot of valuable diagnostic information (see section 3).

Beta parameters are of interest because they enable the shape of variance to be described. For the beta-binomial model, mean and variance are calculated from:

$$\mu = \frac{n\ a}{a+b}$$

$$\sigma^2 = \frac{n\ a\ b\ (n+a+b)}{(a+b)^2\ (1+a+b)}$$

These principles and calculations are illustrated in an example.

Example The Beta-Binomial Model Applied to Car Trips

All 300 consumers are able to reach their principal destination by driving a car or by some other means of travel. The choices are observed for 24 weeks (n=24) and a frequency count is made. Thus 117 consumers never choose a car, 25 consumers choose a car on one occasion, and so on (table 1.1).

The distribution includes several distinct types of consumer: 39% never choose car because the household does not possess a private vehicle or because a car is unavailable. About 12% of the sample choose to travel by car once or twice; in the usual course of events no car is available, though occasionally a friend will act as a chauffeur. At the other end of the distribution, 19% choose car on 19 to 24 occasions. This last group are captive users; they always have access to the family car. Between these 'never-always' extremes less than one third of shoppers select car travel on 3 to 18 occasions out of 24 weeks. Often the family car is available, but this cannot be guaranteed.

Apart from maximum likelihood estimation, beta parameters a and b can be found by the method of moments or the method of mean and zeros. Where there is a reverse J-shaped distribution of choice probabilities (ie. many trips when a car is never chosen) the method of mean and zeros is recommended. The procedure is outlined by Chatfield and Goodhardt (1970, appendix) and is initiated by the observed mean and observed variance.

In the present example the mean frequency is 7, observed variance is 74 and the observed proportion of zeros is 39%. Estimated values for parameters a and b are 0.19 and 0.45 respectively. Using these parameters the proportion of shoppers who choose to travel by car on exactly r out of n weeks is calculated, and column 3 of table 1.1 shows the beta-binomial predicted proportions.

The beta-binomial distribution may take a variety of shapes, but

Table 1.1

The Beta - Binomial Distribution Fitted to the Frequency of Car Choices

Number of occasions when car is chosen	Observed frequency	Beta-Binomial predicted proportions	Discrepancy between observed & predicted proportions
0	117	117	-0.1
1	25	23	-2.3
2	11	14	2.8
3	9	10	1.3
4	9	9	-0.5
5	8	7	-0.7
6	7	7	-0.5
7	6	6	-0.1
8	5	6	0.5
9	5	5	0.2
10	4	5	1.0
11	4	5	0.8
12	4	5	0.7
13	5	5	-0.4
14	4	4	0.5
15	5	4	-0.5
16	4	5	0.6
17	6	5	-1.3
18	5	5	-0.1
19	8	5	-2.9
20	9	6	-3.5
21	8	6	-1.8
22	9	7	-1.7
23	9	10	0.8
24	14	21	7.1
Mean	7	7	
Variance	74	76	

n = 24 weeks
N = 300 consumers
beta parameters
a = 0.19
b = 0.45

characteristically there are two general forms. As r increases from 0 to n, so there is a monotonic decline in probabilities and a low estimated mean (mode at 0). Alternatively a U shaped distribution is obtained. It is a U shaped distribution that we see in the example: the bulk of shoppers rarely choose car, but a significant number are always able to choose car. Choice probabilities are bunched at 0 and n. Mean frequency and variance for the beta-binomial model are 7 and 76 respectively. Both these values are virtually identical to observed values.

A rough indication of goodness of fit is shown by the discrepancy between observed and beta-binomial probabilities (column 4 of table 1.1). At a frequency of 1.3 the mean absolute discrepancy is low, though the fit is not perfect. The theoretical beta-binomial distribution over-predicts the number of car choices in 24 weeks, largely because of a significant under-prediction of car choices over 19 to 23 weeks. Overall, the observed frequency is less accentuated than the predicted proportions

If the only influences upon car choice were unobserved, the beta-binomial model would be adequate. Under such circumstances all heterogeneity is ascribed to unobservables, yet in practice many omitted variables need not be unobserved. People can be asked about their disposable income or whether they hold a current driving licence. People's attitudes are measurable from psychological scaling techniques and repertory grids. Information about the socio-economic features and attitudes of a sample may contribute towards an account of sample variance, leaving heterogeneity due to omitted variables or truly unmeasurable tastes to be described by the beta mixing distribution. Before considering these extensions some justification for the beta distribution is provided.

The beta-binomial model has been used for many years to describe variance discrepancy. It has long been noted that standard binomial models often fail to fit data perfectly and that variation in the sample underlies this discrepancy. A formal model was proposed by Chatfield and Goodhardt (1970) and has been used in the example above.

In the context of discrete choice modelling the beta distribution is particularly appropriate because: it lies in the unit interval, it is flexible, and it affords graphic presentation of results. If purchase incidence is studied the gamma distribution is appropriate, but this has proved to be more problematic in descriptive models. Where the number of choices is greater than two, the beta distribution generalises to the multinomial-beta or Dirichlet distribution (Jeuland et al. 1980, Goodhardt et al. 1984).

Apart from these desirable properties, there are additional reasons why models based on the beta distribution are a sensible choice.

(a) Empirical success, for purely stochastic versions, has been demonstrated in many areas of research and application, from the analysis of brand selection to store choice (Jeuland et al. 1980, Goodhardt et al. 1984, Kau and Ehrenberg 1984). See also Wrigley and Dunn (1984b, 1984c).

(b) Extensions to encompass logistic models have been proposed, thereby forging strong links between cross-sectional decision theory and stochastic process theory. These links are most apparent in econometrics (Heckman and Willis 1977, Heckman 1981a), though they are evident elsewhere (Dunn and Wrigley 1985, Jones and Zufryden 1980, 1982).

(c) Parameter estimates can be obtained from the method of maximum likelihood. Estimates are available both for two-alternative and many-alternative choice problems. Dunn and Wrigley (1985) were the first to develop and estimate the many-alternative form and have referred to their extension as the Dirichlet-logistic model. Applications of the Dirichlet-logistic model were confined to store-choice in the first instance; the results given in the next few sections will show that further extensions to model travel and activity choices are equally successful.

(d) The parametric form allows a variety of goodness of fit and diagnostic procedures to be undertaken. In so doing, panel data methods are tied into wider debates surrounding model specification, robustness and goodness of fit in discrete choice and duration models. Complementary approaches are found in econometrics (Lancaster and Nickle 1980, Chesher 1984).

Through a series of examples points (a) to (d) are elaborated; in particular, the nature of true heterogeneity is separated from spurious statistical effects. Links with cross-sectional logistic models are emphasised, and attention is given to model specification, and goodness of fit.

2 Heterogeneity in Zero - Order Models

The role of heterogeneity in the analysis of panel data is investigated. A start is made by examining binary choice. On successive occasions one of two forms of travel is chosen, and the number of these occasions varies across the sample. Next, a multi-choice situation is considered: several forms of travel can be selected on successive occasions and again the number of occasions may vary. Finally, analysis is extended to bundles of activity which are repeatedly occupied within a fixed time period.

2.1 The Beta - Logistic Model

We have seen how the beta mixing distribution may be incorporated into a binomial model and that where choice probabilities vary across a sample the beta-binomial model will predict travel by car in r weeks out of n. To derive the beta-binomial distribution two empirical parameters were found, a and b, and for simplicity these were calculated by the method of mean and zeros.

Beta parameters, in fact, can be estimated by maximum likelihood methods and this allows existing models to be extended. Let the beta parameters be functional estimates of exogenous variables. In particular, assume a logistic function such that the choice probabilities are conditioned on time-invariant exogenous variables. Then, following Heckman and Willis (1977), the functional form is:

$$a = e^{\underset{\sim}{x}'\underset{\sim}{\alpha}} \qquad\qquad b = e^{\underset{\sim}{x}'\underset{\sim}{\beta}}$$

where x' is the vector of exogenous variables, and $\underset{\sim}{\alpha}$ and $\underset{\sim}{\beta}$ are vectors of estimated parameters.

The beta-binomial model is re-written to take account of observed variation (perhaps travellers are asked about car ownership or the bulkiness of goods that they carry). The probability of choosing car on r occasions from n weeks, conditional on exogenous variables, is

$$p_r = \frac{\Gamma(n+1)}{\Gamma(r+1)\ \Gamma(n-r+1)} \ \frac{\Gamma(e^{\underset{\sim}{x}'\underset{\sim}{\alpha}}+r)\ \Gamma(e^{\underset{\sim}{x}'\underset{\sim}{\beta}}+n-r)}{\Gamma(e^{\underset{\sim}{x}'\underset{\sim}{\alpha}}+e^{\underset{\sim}{x}'\underset{\sim}{\beta}}+n)} \ \frac{\Gamma(e^{\underset{\sim}{x}'\underset{\sim}{\alpha}}+e^{\underset{\sim}{x}'\underset{\sim}{\beta}})}{\Gamma(e^{\underset{\sim}{x}'\underset{\sim}{\alpha}})\ \Gamma(e^{\underset{\sim}{x}'\underset{\sim}{\beta}})}$$

Aspects of heterogeneity are derived by substituting the logistic form into earlier estimates of moments. Thus, the mean (expected) probability of choosing car travel in any week becomes:

$$\text{mean}(p) = \frac{a}{a+b} = \frac{e^{\underset{\sim}{x}'\underset{\sim}{\alpha}}}{e^{\underset{\sim}{x}'\underset{\sim}{\alpha}}+e^{\underset{\sim}{x}'\underset{\sim}{\beta}}}$$

Higher moments are

$$\mathrm{var}(p) = \frac{a\,b}{(a+b)^2(a+b+1)} = \frac{e^{\underset{\sim}{x}'\underset{\sim}{\alpha}} \cdot e^{\underset{\sim}{x}'\underset{\sim}{\beta}}}{(e^{\underset{\sim}{x}'\underset{\sim}{\alpha}}+e^{\underset{\sim}{x}'\underset{\sim}{\beta}})^2(e^{\underset{\sim}{x}'\underset{\sim}{\alpha}}+e^{\underset{\sim}{x}'\underset{\sim}{\beta}}+1)}$$

$$\mathrm{mode}(p) = \frac{a-1}{a+b-2} = \frac{e^{\underset{\sim}{x}'\underset{\sim}{\alpha}}-1}{e^{\underset{\sim}{x}'\underset{\sim}{\alpha}}+e^{\underset{\sim}{x}'\underset{\sim}{\beta}}-2} \qquad \text{if } a,b > 1$$

Interpretation of moments is fairly straight-forward. The mean probability depends on the relative values of the beta parameters (ie. is 'a' larger, smaller or equal to 'b' ?). The mode and variance, by contrast, depend on absolute values of the beta parameters (ie. what are the individual sizes of 'a' and 'b' ?). These higher moments - mode and variance - are used to diagnose heterogeneity that arises from unmeasurables and omitted variables.

Dunn and Wrigley (1985) provide a useful table to show the relationship between relative and absolute values of the beta parameters and a version is shown as table 2.1. Notice that the table can be used as an indicator chart to read off distinctive shapes of the beta distribution. Where both a and b are less than one the distribution is humpbacked with a single mode, where both a and b are greater than one the distribution is bimodal and U shaped, and so on.

Graphic presentation makes these points clearer and a few examples are given in figure 2.1. Homogeneity is assumed in the first instance: the mean probability is equivalent to the actual probability, consequently there is no variation around the mean.

Far more common are the situations shown next. Example (b) shows a U shaped form, where choice probabilities due to omitted variables have concentrated at the extremes of the unit interval. One interpretation might be that shoppers reach a city centre shopping arcade always by bus or never by bus, and few shoppers will alternate between these alternatives.

The J shaped curve in example (c) has a mode at 1.0 which suggests that shoppers always select the alternative under study - always driving to a freezer centre for example. Negligible numbers deviate from the norm. Further discussion and interpretation of the beta distribution is reserved until empirical estimates have been calculated (later in section 2.1).

Before going on to apply this body of theory, the link with conventional cross-section logit needs to be stated. The mean probability of choosing an alternative is:

$$\mathrm{mean}(p) = \frac{e^{\underset{\sim}{x}'\underset{\sim}{\alpha}}}{e^{\underset{\sim}{x}'\underset{\sim}{\alpha}}+e^{\underset{\sim}{x}'\underset{\sim}{\beta}}} = \frac{e^{\underset{\sim}{x}'(\underset{\sim}{\alpha}-\underset{\sim}{\beta})}}{1+e^{\underset{\sim}{x}'(\underset{\sim}{\alpha}-\underset{\sim}{\beta})}}$$

Table 2.1

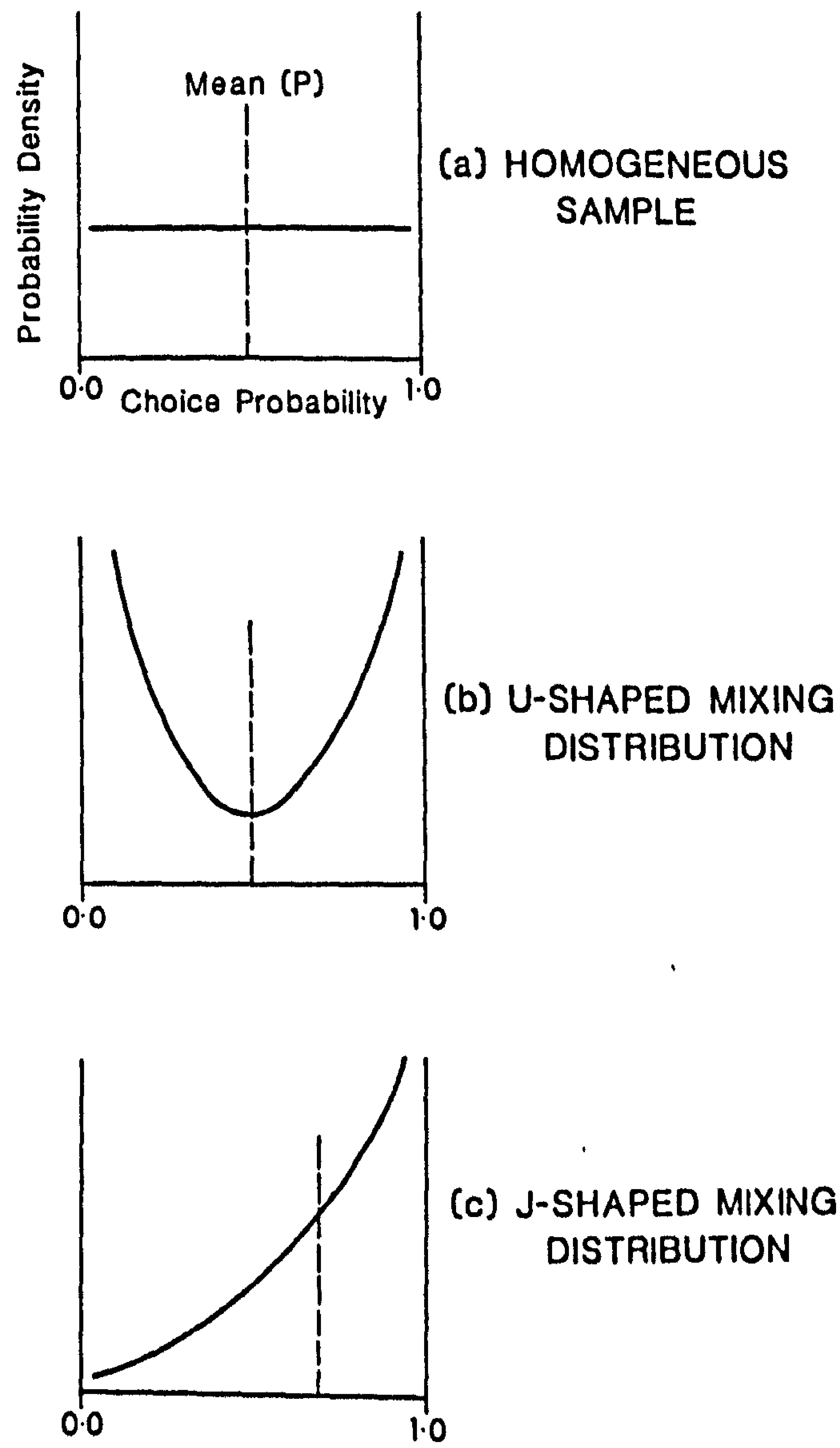
Characteristics of the Beta 'Mixing' Distribution

(From Table 1, Dunn and Wrigley 1985)

	Value of: a	b	Shape of Beta Distribution
Absolute values	>1	>1	unimodal, humpbacked
	<1	<1	bimodal, U shaped
	>1	<1	unimodal, J shaped (mode at 1)
	<1	>1	unimodal, reverse J shaped (mode at 0)
	=1	=1	rectangular
Relative values	a = b		symmetric
	a > b		negatively skewed
	a < b		positively skewed

Figure 2.1

POSSIBLE BETA "MIXING" DISTRIBUTIONS



Heckman and Willis (1977) recognise this as a logit function with coefficient vector $\underset{\sim}{\gamma}=\underset{\sim}{\alpha}-\underset{\sim}{\beta}$. These authors go on to state that:

> 'With cross-section data (ie. data on participation for only 1 year), $\underset{\sim}{\beta}$ and $\underset{\sim}{\alpha}$ cannot be identified separately. Hence, the ordinary logit function can be used only to predict the mean participation rate in a population conditional on the x's, but cannot determine the higher moments of the distribution of participation probabilities.' (Heckman and Willis 1977,41).

Example 1 A Dichotomous Model:

Mode Choice on All Trips

Over 4 weeks the behaviour of 300 consumers is observed; this length of study period is chosen for clarity of exposition. These consumers, drawn from the Cardiff consumer panel, have two alternative ways to reach shops. The first way is to drive by car. Personalised and flexible, car travel enables shops at most locations and at most times during the working day to be reached. Only in the central area do parking restrictions control the amount of movement. All other alternatives - pedestrian and public transport - are grouped together. Discretionary movement is lower because of tight schedules on public transport and because of the physical difficulty of carrying bulky goods. Invariably district and local centres are patronised.

The quantal response variable is defined for all grocery and convenience-goods trips made in the period February 8 to March 7 1982. Within the fixed observation period individual rates of trip making vary: a typical shopper might walk to nearby shops on 11 occasions, travel by bus on 4 occasions, and make 11 trips by car. In this instance a total of 26 trips is recorded - 11 allocated to alternative one and 15 to the second alternative.

Each person's travel behaviour is regarded as a series of n Bernoulli trials, and on each 'trial' there is a probability of selecting one form of travel. Across persons the number of n trials will vary: 26 trips, 5 trips, etc. Unbounded n implies a model similar to that developed by Pyatt (1969). Pyatt's formulation is versatile but does not provide measures that are suitable for model assessment, consequently in sections 2.3 and 3.1 versions with constant bounded n are employed.

A large number of influences act upon the decision process. Some trips involve nothing more than 'topping-up' at convenient local stores and it is feasible to walk. Others give rise to carriage problems and choice becomes centred around car travel. Much variation is evident too: elderly shoppers often find trips tiring and select bus travel even for short distances, others have easy access to the family car. Five exogenous variables are included in the current model: household income and size (both ordinal), and three binary dummy variables to define work status, deep freezer ownership, and whether the consumer is elderly.

Household income is a 7 category variable ranging from under £2,000 to over £15,000 and with a mode at £3-4,000. Some 67 households lie at the mode, while 12 and 14 households occupy the lower and upper extremes respectively. Correspondence with distinctive study areas is marked: the inner city areas of Cathays and Roath show a preponderance of low and average income households; considerably wealthier are many households in the private suburban districts of Rhiwbina and Heath. Rising income makes car travel more attractive (or affordable), and this becomes evident in personal utility functions and decision-making.

Size of household determines the amount of shopping activity that has to be undertaken. Size also affects quantities carried home and in so doing it influences mode choice. The variable for household size has a bimodal shape: 2-member and 4-member families are each represented by 74 households (ie. 25% of the sample). This variable not only affects shopping behaviour, it shapes distinctive life-styles

Working status makes an indirect contribution to family income, but far more important is its influence on the valuation of time and the efficient organisation of activity. Full-time work leaves less scope for family maintenance activities and encourages the use of car travel, especially to reach edge-of-town superstores and hypermarkets where all goods are purchased on one occasion. Ideally those who work full-time should be kept apart from part-time workers, but to maintain equality in the relative number of binary responses a crude distinction between work / no work is used. Some 43% of the sample work part-time or full-time.

The binary variable for deep freezer ownership is included because of the relationship between travel-carriage-storage, and the influence that this relationship is expected to have on travel. About 45% of the sample own a separate deep freezer. A variable to characterise elderly travellers highlights their difficulty in reaching desirable destinations. Much concern has been aired about the 'double deprivation' that elderly persons face, owing to personal immobility and inadequate local shops. Elderly persons, aged 65 or more, are 33 in number.

Three supplementary points ought to be noted prior to the discussion of results. First, several variables defined here are characteristics of the household and do not necessarily hold true for individual members. Family members certainly will not have an equal share of disposable income, and disposable income itself will vary across families as a proportion of total income. It is important, therefore, to include person-specific variables such as working status and whether elderly.

Second, experimentation with attitudinal variables was undertaken. Looked at were people's attitude to shopping just once a week and whether they felt that shopping for groceries is tiring. Both these attitudes were expected to reduce overall trip incidence and encourage car travel. Neither expectation was upheld.

Thirdly, to avoid inferential difficulties no alternative-specific factors, such as fares charged on buses or costs of petrol for car drivers, are included. All variables are truly exogenous. The complete set of exogenous variables defines the vector $\underset{\sim}{x}'$.

The full model of mode choice is estimated by a quasi-Newton optimisation routine, this gives efficient maximum likelihood estimates (Gill et al. 1981). NAG subroutine E04JBF is called (see Acknowledgements), estimates from which are presented in table 2.2.

Notice first the parameter estimates α and β shown in columns 1 and 2. As household income rises so the probability of choosing to travel by car increases and the propensity to travel by other means falls. Falling propensities among non-car modes are not dramatic. It is possible that within the 'catch-all' alternative not all choices of mode are equally sensitive to variations in income. The multi-choice example (section 2.2) will clarify this issue. Conversely the influence of deep freezer ownership on car choice is negligible and equivocal, whereas it weighs strongly against personal and public transport. Bulky produce for the freezer is not easy to carry when the shopper is walking or riding by bus.

Below each parameter estimate is the asymptotic t value. At conventional significance levels ($t>1.9$) a mixture of significant and less significant estimates are observed. These are as expected. The values of t associated with household income, for instance, are highly significant against choice of car, and definitely insignificant against other modes.

Overall, t values are consistently higher for parameter estimates in column 1. It is suggested that the model includes important predictors of car travel, but is less discriminating when attention turns to other modes. Alternative-specific variables, such as waiting time, comfort, duration of journey, and fares, may be particularly important when other modes are studied; none of these are represented here.

Various tests are available to assess the contribution of each exogenous variable. Heckman and Willis (1977) assess each exogenous variable against mean predicted probabilities; this defines 'partial effects'. Specifically, the partial effect of an exogenous variable equals $(\alpha-\beta)m(1-m)$ where α and β are appropriate parameter estimates and m is the mean predicted probability of car travel, which in this example is 0.31. Looking at column 3 of table 2.2 it is clear that income and deep freezer ownership have major positive effects, and household size acts moderately strongly in a negative direction. Working status and the elderly dummy variable contribute least.

Table 2.2

Maximum Likelihood Estimates for a Dichotomous Model of Mode Choice

Variable	Parameter estimates $\underset{\sim}{\alpha}$	$\underset{\sim}{\beta}$	Partial effect	Likelihood ratio test	Significance level
Constants	-2.40 (5.6)	0.36 (0.8)			
Income	0.50 (6.7)	-0.05 (0.6)	0.12	88	99 %
Size	-0.15 (1.9)	0.04 (0.4)	-0.04	9	98 %
Deep freezer	-0.03 (0.1)	-0.57 (2.5)	0.12	11	99 %
Working status	0.23 (1.1)	0.15 (0.6)	0.02	1	-
Elderly	0.55 (1.3)	0.59 (1.2)	0.01	2	75 %

Sample of travelling consumers 300
Asymptotic t values in parentheses
Partial effects defined from $(\alpha-\beta)m(1-m)$, where
m = mean predicted probability of car travel
Likelihood ratio test distributed as χ^2 with
2 degrees of freedom

An alternative test is available from the likelihood statistics. Each variable is dropped in turn from the full model to give a set of 10-parameter models. The likelihood ratio between complete and 10-parameter models is a test statistic distributed as χ^2 with 2 degrees of freedom (one degree for each parameter removed).

Results and significance levels for these tests are shown in columns 4 and 5 of table 2.2. Household income is extremely significant; while size, deep freezer and whether elderly are acceptable. The dummy variable for working status performs badly: working status may be truly uninfluential or the behaviour of part-time workers may obscure real differences between those engaged in full-time employment and those not in the workforce.

2.1.1 Heterogeneity

Earlier we alluded to the importance of higher moments; in particular the shape and moments of the beta mixing distribution were used to describe the heterogeneity that arises from unobservables. Now a more detailed appraisal is made: we describe the heterogeneity that arises from unobservables for specific types of consumer.

To illustrate the discussion consider a single elderly person with moderate income and a deep freezer. Associated with each of these attributes are parameter estimates (taken from table 2.2); summing over these estimates and finding exponents gives individual a_i and b_i terms. Each household type i has a mean (expected) probability of choosing to travel by car:

$$\text{mean}(p_i) = \frac{a_i}{a_i + b_i}$$

For the elderly household, calculations of a_i and b_i are shown in the first two columns of table 2.3 (against household type 1). Figures for some other types are depicted too. Two are single person households which represent the extremes of the adult life-cycle: affluent-single-young-working and single-elderly-retired. In contrast, the three remaining types characterise larger families: nuclear with working shopper, large with many children, and an elderly couple. Elderly low income types are typically domicile in the inner city area of Roath, nuclear and large families concentrate in the private and public estates of the city periphery, and moderately wealthy old persons tend to live in the prosperous private area of Heath.

Comparison of expected probabilities for these different types reveals a 0.57 chance of choosing car travel among moderately wealthy old persons (type 1), which is considerably above probabilities for low income elderly couples (type 6) and younger single persons living off a low income (type 2). The expected probability of car travel is much higher among affluent single persons and high income nuclear families (types 3 and 4), being 0.60 and 0.76 respectively.

Table 2.3

Characteristics of the Mixing Distribution for a Dichotomous Model of Mode Choice

Household type	a_i	b_i	Mean(p_i)	Mode(p_i)	Var(p_i)
1	1.60	1.19	0.57	0.76	0.06
2	0.21	0.76	0.22	bimodal	0.09
3	1.16	0.76	0.60	1	0.08
4	2.34	0.75	0.76	1	0.04
5	0.74	1.35	0.35	0	0.07
6	0.52	2.41	0.18	0	0.04

Definition of Household Types

Type	Income	Size	Deep freezer	Working	Elderly
1	moderate	single	yes	no	yes
2	low	single	yes	no	no
3	moderate	single	yes	yes	no
4	high	nuclear	yes	yes	no
5	high	large	no	no	no
6	low	couple	no	no	yes

Figure 2.2

MIXING DISTRIBUTIONS FOR DIFFERENT HOUSEHOLD TYPES IN THE DICHOTOMOUS MODEL

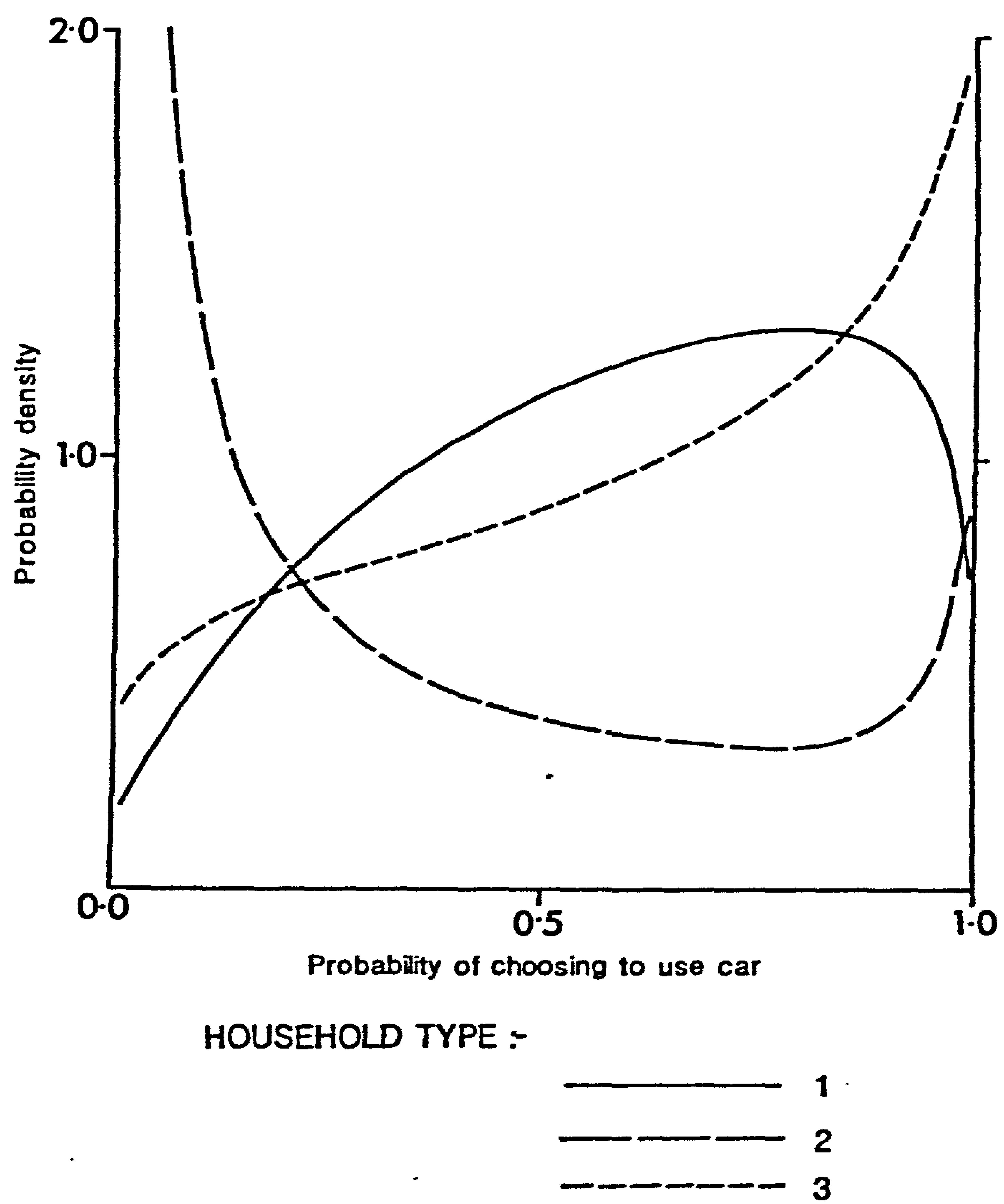
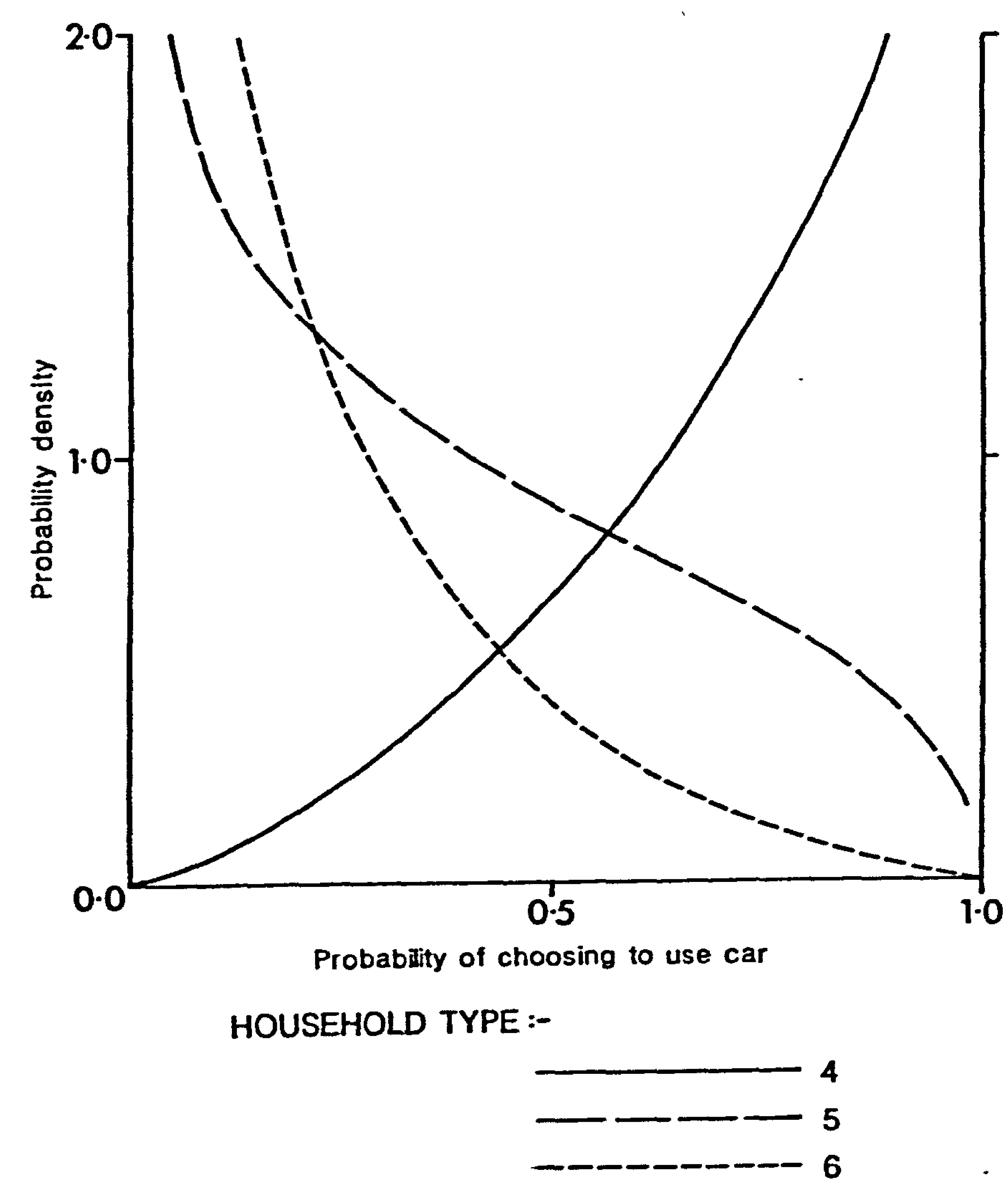


Figure 2.3

MIXING DISTRIBUTIONS FOR DIFFERENT HOUSEHOLD TYPES IN THE DICHOTOMOUS MODEL



Presented in the final two columns of table 2.3 are the higher moments. As expected, given the value of mean probabilities, household type 4 has a mode at 1 (the most likely choice is car travel) and household type 6 has a mode at 0 (another form of travel is most likely). Variance is low (0.04) in both cases. Other types are more ambiguous, for instance type 2 has a large variance (0.09) and exhibits a bimodal distribution.

The features of the mixing distribution are clearer when heterogeneity is plotted, as demonstrated by Dunn and Wrigley (1985). Figures 2.2 and 2.3 provide graphic depictions of choice probabilities for each of the 6 household types discussed above. Household type 1 describes a humpbacked shape with a single mode at 0.76. Cross-section models implicitly assume unimodality and a rapid decline of probabilities about the mode, whereas for household type 1 probabilities are spread out.

Households 2 and 3 depict very different forms of heterogeneity. The former is U shaped or bimodal, although the positive skew indicates a dominant tendency not to travel by car. Household 3, by contrast, is J shaped with a mode at 1 and shows a definite propensity to select car travel. Time spent shopping is minimised, there is ready access to a car for shopping purposes, and bulk goods can be stored easily.

The only other form of distribution picked out at this stage is the unimodal reverse J shape which characterises households 5 and 6 in figure 2.3. For both large families and elderly couples grocery shops are reached on foot and by public transport. In neither of these households does the principal shopper work (so pressure on time is not too great) nor is a deep freezer owned (so few items are bought in bulk and trip frequencies are high).

2.2 The Dirichlet - Logistic Model

Where there are more than two choice alternatives, the beta and logistic distributions are replaced by their multivariate equivalents, viz. the Dirichlet and multinomial distributions respectively. A full exposition of the multivariate model is given by Dunn and Wrigley (1985) and only a summary is outlined here.

Let r be the number of occasions in a period of n weeks that a particular choice is made. The particular choice is denoted by j and there are j = 1,2,...,J alternatives. The multivariate equivalent of the beta-binomial distribution has the form:

$$p_r = \binom{n}{r_1,\ldots,r_J} \frac{\Gamma(S)}{\Gamma(S+n)} \prod_{j=1}^{J} \left[\frac{\Gamma(a_j+r_j)}{\Gamma(a_j)} \right]$$

S in this formula is the sum of Dirichlet parameters over all alternatives ($S = a_1, a_2, \ldots, a_J$). Effectively S is an 'all choices' or 'superchoice' alternative. This gives a most convenient result: the probability of choosing alternative j has the j^{th} marginal distribution in the Dirichlet-logistic model and this marginal distribution is the beta.

Such a simplification of the multivariate problem means that tractable and efficient solutions are available. There is an analogy here with multinomial logit models and similar assumptions underpin these models. Especially important where consumers face several alternatives is the assumption that: the predicted number of occasions when alternative j is chosen is independent of remaining occasions when all other alternatives are chosen.

Goodhardt et al. (1984, 2.2) neatly summarise the assumption when they write that 'for two brands j and k, p_j and $p_k/(1-p_j)$ should be independent rather than p_j and p_k'. When market researchers say that the market is 'unsegmented' this assumption is what they have in mind. More generally, the axiom of 'independence from irrelevant alternatives' is mentioned. Opinions differ as to the suitability of this assumption - the debate is central (and controversial) in the rational choice literature, but further comment is not supplied here (for a critical review see Aitchison 1982).

Just as the beta parameters can be expressed as functions of exogenous variables, so also can the Dirichlet parameters. A series of logistic functions are specified:

$$a_1 = e^{\tilde{x}'\tilde{\alpha}_1}$$

$$a_2 = e^{\tilde{x}'\tilde{\alpha}_2}$$

$$\vdots$$

$$a_J = e^{\tilde{x}'\tilde{\alpha}_J}$$

where x' is a vector of exogenous variables and $\tilde{\alpha}_j$ is a vector of parameter estimates for the j^{th} alternative.

All moments are similar to those given for models where there are only two alternatives. The mean (expected) probability of choosing alternative j is expressed as a share (or 'market share'):

$$\text{mean}(p_j) = \frac{a_j}{S} = \frac{e^{\tilde{x}'\tilde{\alpha}_j}}{\sum_{s=1}^{J} e^{\tilde{x}'\tilde{\alpha}_s}}$$

The variance and mode of the Dirichlet distribution are:

$$\mathrm{var}(p_j) = \frac{a_j(S-a_j)}{(S)^2(S+1)} = \frac{e^{\underset{\sim}{x}'\underset{\sim}{\alpha}_j}\left(\left\{\sum_{s=1}^{J} e^{\underset{\sim}{x}'\underset{\sim}{\alpha}_s}\right\} - e^{\underset{\sim}{x}'\underset{\sim}{\alpha}_j}\right)}{\left(\sum_{s=1}^{J} e^{\underset{\sim}{x}'\underset{\sim}{\alpha}_s}\right)^2 \left(\left\{\sum_{s=1}^{J} e^{\underset{\sim}{x}'\underset{\sim}{\alpha}_s}\right\} + 1\right)}$$

$$\mathrm{mode}(p_j) = \frac{a_j - 1}{S - 2} = \frac{e^{\underset{\sim}{x}'\underset{\sim}{\alpha}_j} - 1}{\left(\sum_{s=1}^{J} e^{\underset{\sim}{x}'\underset{\sim}{\alpha}_s}\right) - 2} \qquad \text{if } a_j < 1,\ S > 2$$

The relative values of a_j and S are used to define the mean probability for a single alternative j. A cross-sectional model - such as multinomial logit - can give only these most basic predicted probabilities. Whereas in the longitudinal model absolute values of Dirichlet parameters are available to define mode and variance. In so doing the form of heterogeneity which arises from omitted variables and unmeasurables is described.

Example 2 A Polychotomous Model: Mode Choice on All Trips

In discussion of the previous example it was suggested that differences between walking and public transport might be as important, if not more important, than differences between car and all other modes. As an illustration of the polychotomous form (ie. the Dirichlet-logistic model) we shall address this topic of choice between car, walk and public transport.

Most features of the previous example are unchanged. There are 300 individuals whose choice of mode is observed over 4 weeks. All trips to grocery and convenience shops are recorded; these are used to define the quantal response. Recall that the total number of trips varies across individuals, and that trips may be localised emergency visits, or major infrequent visits to edge-of-town superstores, or grocery shops visited on the return-journey from work.

Again five exogenous variables are included: household income and size (both ordinal) and three binary dummy variables for working status (part-time and full-time versus not working), deep freezer ownership (present or absent), and whether the consumer is elderly (yes or no).

Table 2.4 provides details of the polychotomous model of mode choice. Parameter estimates, obtained by the method of maximum likelihood, are shown in columns 1 to 3 for each of j = 1,2,3 choice alternatives. The $\underset{\sim}{\alpha}_j$ terms are multiple versions of the

Table 2.4

Maximum Likelihood Estimates for a Polychotomous Model of Mode Choice

Variable	Parameter estimates $\underset{\sim}{\alpha}_1$ Car	$\underset{\sim}{\alpha}_2$ Walk	$\underset{\sim}{\alpha}_3$ Bus	Likelihood ratio test	Significance level
Constants	-2.37 (5.8)	0.19 (0.5)	-1.15 (2.9)		
Income	0.52 (7.0)	-0.03 (0.4)	-0.12 (1.6)	101	99 %
Size	-0.17 (2.2)	0.04 (0.5)	-0.01 (0.1)	11	98 %
Deep freezer	0.17 (0.9)	-0.32 (1.6)	-0.03 (0.1)	9	96 %
Working status	0.31 (1.5)	0.23 (1.1)	0.43 (1.9)	4	80 %
Elderly	0.24 (0.6)	0.04 (0.1)	0.40 (1.1)	2	-

Sample of travelling consumers 300
Asymptotic t values in parentheses
Likelihood ratio test distributed as χ^2 with 3 degrees of freedom

alpha parameters encountered earlier. So, a rise in household income increases the probability of choosing to travel by car and considerably lessens the propensity to travel by bus: these outcomes are typical for superior and inferior goods respectively.

The impact on pedestrian movement is equivocal. The inclusion of minor visits to local stores means that walks remain important regardless of income. Walks tend to be spontaneous. However, walks are often regarded as inefficient and this is borne out by the deep freezer variable: ownership of a deep freezer reduces the probability that walking is undertaken ($\alpha_2 = -0.32$) and raises the probability of car travel ($\alpha_1 = 0.17$). Where a freezer is owned,goods can be bought in bulk, carried home by car, and stored in large capacity spaces.

Below each parameter estimate is the asymptotic t value. At conventional significance levels the estimates are supported to varying degrees: income is most significant as a predictor of car choice, whereas working status is most significant as a predictor of bus travel. Presumably many who work, and who travel by bus, shop on the journey home.

Each variable is assessed by inspection of likelihood ratios. The likelihood ratio test statistic is distributed as χ^2 with 3 degrees of freedom (one degree of freedom for each parameter removed). Test results are shown in columns 4 and 5 of table 2.4. Household income is extremely significant, convincing too are ratios for household size, deep freezer ownership and work status. The dummy variable to indicate whether the consumer is elderly is not significant.

2.2.1 Heterogeneity

Turning to the spread of choice probabilities across the sample of Cardiff consumers, we again focus on a select number of household types. Type 1 is a low-income elderly person living alone. Associated with the variable for the elderly is a high parameter estimate for bus travel, so type 1 individuals are more likely to choose bus travel on all trips except very local ones. Local visits themselves are dominated by walks.

Mean probabilities listed in column 3 of table 2.5 bear out these comments. The mean probability of bus travel is 0.22 for household type 1. A mean of 0.22 is high for such an unpopular mode of travel, though for walks the probability is 0.69. With a mode at 1, walk-based trips have a unimodal choice probability, while bus and car travel are both bimodal. The double deprivation that faces many elderly people is evident: reliance on public transport confines movement to local facilities where prices are sometimes higher and where the product range is narrower.

Caution must be exercised in making generalisations. Some variances reach 0.08, which is quite high, and generalisation is difficult. The plots displayed in figure 2.4 emphasise the range of variation: the probability of bus travel describes a J shaped curve with a single mode at 1, both other choices are positively skewed U shapes, and car choice almost has a mode at 0. To reiterate a point made earlier, the low 'choice' of reaching shops by car most likely arises from inaccess and unavailability rather than from an adversity to travel by car.

A couple with moderate income define household type 2. Walking remains dominant and at a level similar to the first household (ie. mean probability of 0.62, table 2.5). Now bus travel is distinctly less likely and higher income (which implies greater affluence) raises the expected probability of car travel to 0.28.

Variances of 0.07 to 0.08 are moderately high, so we can only talk of predilections for certain forms of travel rather than definite choices. Although, from column 4 of table 2.5 and from figure 2.5, pedestrian trips do show a decisive J shaped curve with a single mode at 1.

A very different level of affluence and life-style is associated with household 3. Income is high (though the household is not large), the principal shopper goes to work (which may give rise to time constraints), but goods can be bought in bulk to be stored in a freezer. Intuitively one would expect members of this group to select car travel: the shopper may have sufficient economic independence to run a car and the constraint on time provides an incentive to shop infrequently at stores best reached by car.

Empirical support for these expectations is found in table 2.5 and figure 2.6. Parameters for deep freezer ownership and paid employment contribute positively to the choice of car, giving a mean probability of 0.74 and a mode that approaches 1. There is less ambiguity in these results: car travel now displaces all alternatives. The mixing distribution for car travel shows a strong negative skew towards the choice probability 1. Bus travel proves to be extremely and consistently unlikely; there is a heavy positive skew giving rise to a reverse J shape and a variance of less than 0.01.

Before leaving these examples one final comment needs to be appended. The decision to study all trips (rather than major trips) underlies a lot of the findings presented in the preceding pages. Car borne trips may be less likely than pedestrian trips because they are infrequent rather than unimportant. Many researchers have preferred to consider principal trips alone and all subsequent investigations of heterogeneity in this chapter follow the same tradition. Hopefully our discussion of both types shows that important insights are to be gained from each perspective.

Table 2.5

Characteristics of the Mixing Distribution for a Polychotomous Model of Mode Choice

Type	a_{ji}	S_i-a_{ji}	Mean(p_{ji})	Mode(p_{ji})	Var(p_{ji})
Household i = 1					
j = Car	0.17	1.68	0.09	bimodal	0.03
j = Walk	1.27	0.58	0.69	1	0.08
j = Bus	0.41	1.44	0.22	bimodal	0.06
Household i = 2					
j = Car	0.53	1.36	0.28	0	0.07
j = Walk	1.17	0.72	0.62	1	0.08
j = Bus	0.19	1.70	0.10	0	0.03
Household i = 3					
j = Car	3.46	1.21	0.74	0.92	0.03
j = Walk	1.01	3.66	0.22	0.04	0.03
j = Bus	0.20	4.47	0.04	0	0.01

Definition of Household Types

Type	Income	Size	Deep freezer	Working	Elderly
1	low	single	no	no	yes
2	average	couple	no	no	no
3	high	nuclear	yes	yes	no

Figure 2.4

MIXING DISTRIBUTIONS FOR HOUSEHOLD TYPE i=1
IN THE POLYCHOTOMOUS MODEL

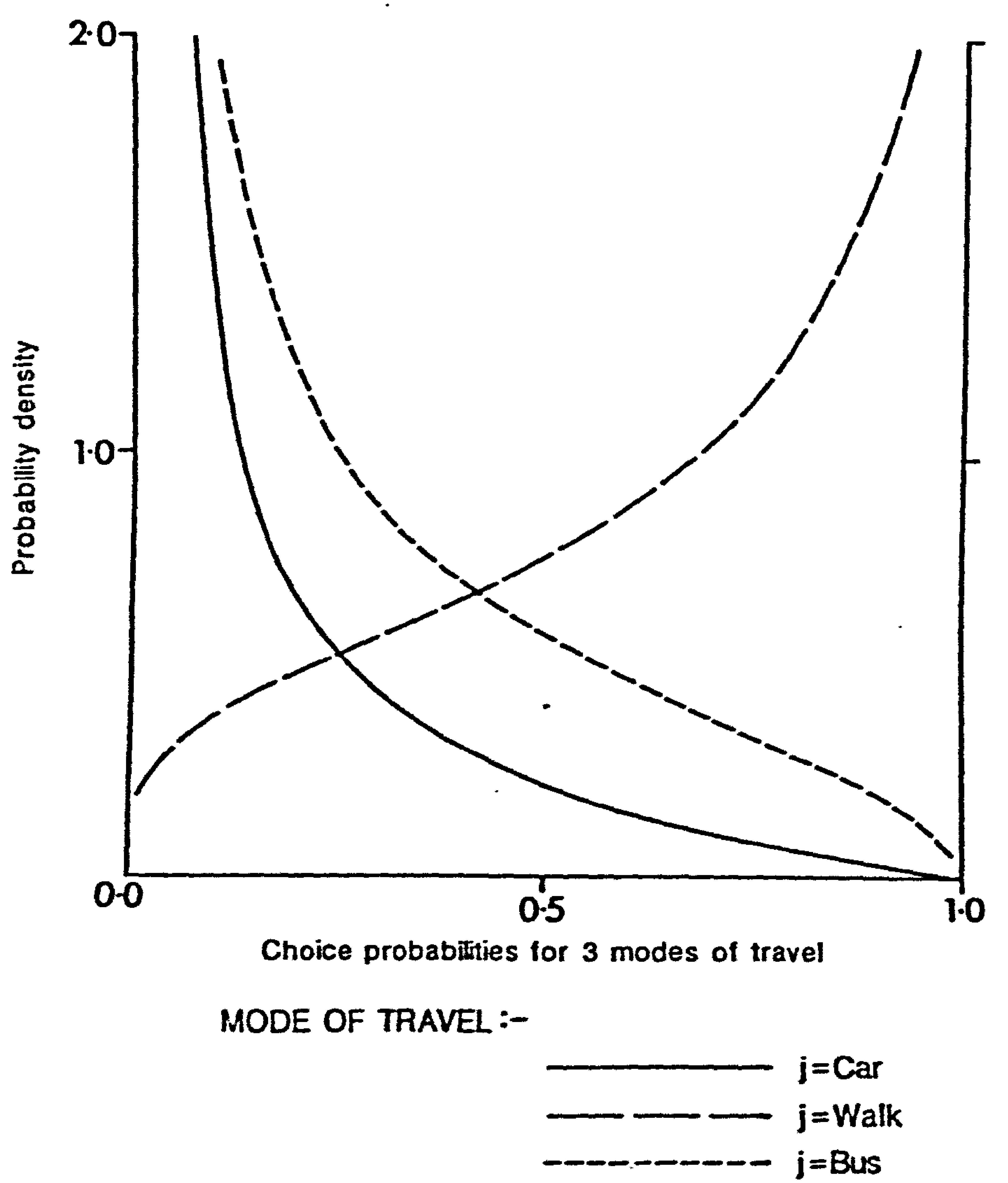


Figure 2.5

MIXING DISTRIBUTIONS FOR HOUSEHOLD TYPE i=2
IN THE POLYCHOTOMOUS MODEL

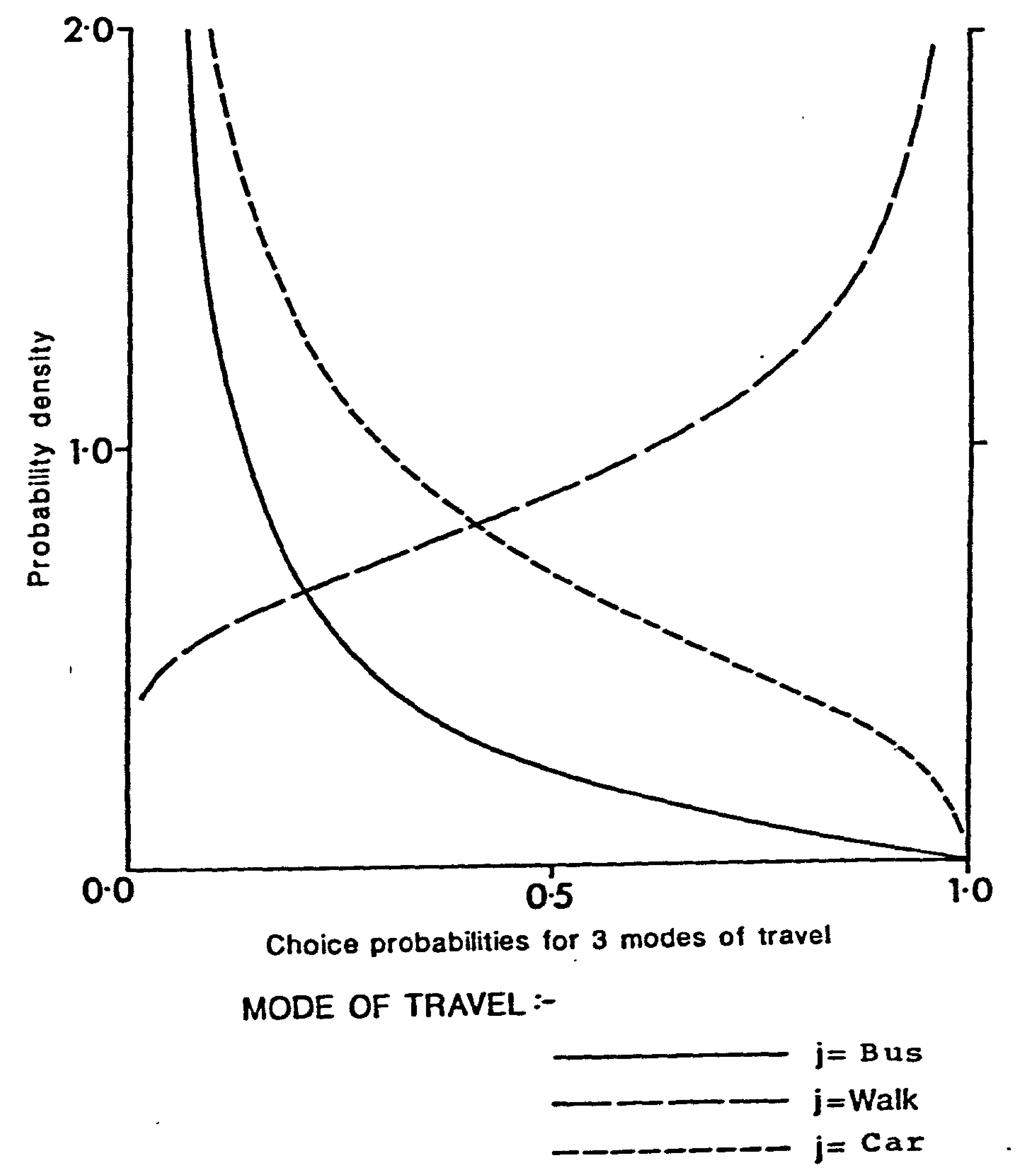
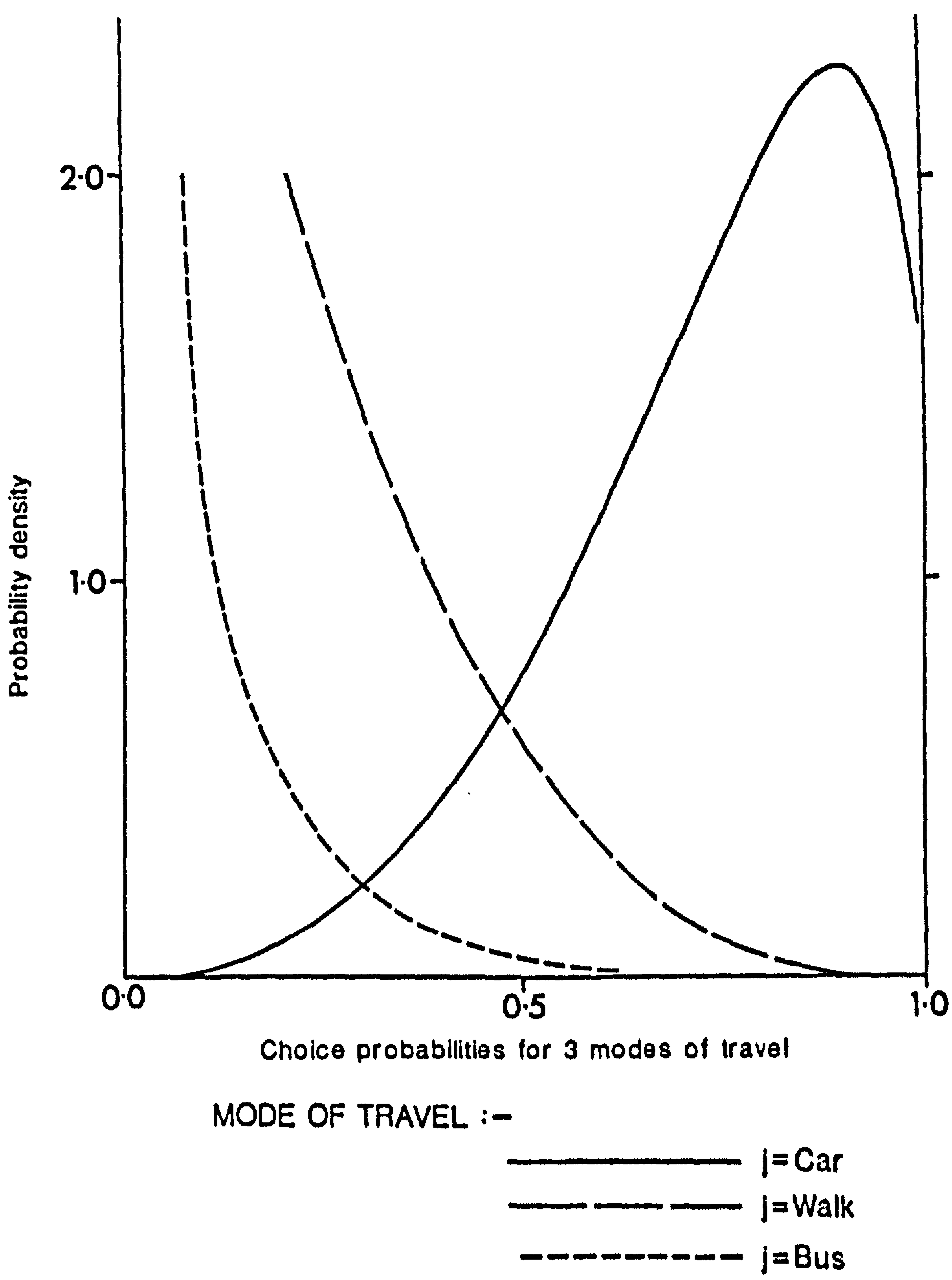


Figure 2.6

MIXING DISTRIBUTIONS FOR HOUSEHOLD TYPE i=3
IN THE POLYCHOTOMOUS MODEL



2.3 Zero - Order Activity Models

The first two examples presented in this chapter drew upon the discrete choice literature. Each alternative was qualitatively distinct and was easily identified, such as the quantal choice between car, bus and walk. Now a number of fuzzier choice alternatives are considered.

Following suggestions made in chapter 3 and by Koppelman and Pas (1983), Golob (1983) and Pas (1984) distinct bundles of shopping activity are viewed as quantal responses.

Principal trips are described by several attributes: number of stops, expenditure, bulkiness of goods and so forth. Using these descriptions, trips are classified into a finite number of bundles. Where the list of attributes includes details of routes, store locations and home locations it is appropriate to talk of activity patterns, in all other circumstances the term 'activity bundles' is customary. Bundles, for example, might distinguish between low expenditure morning trips and heavy expenditure evening trips. Such bundles are regarded as alternative states which may be occupied repeatedly over successive weeks.

In effect, the familiar repeat- choice matrix is replaced by a repeat-activity matrix. Entries in this new matrix take account of the nature of shopping trips - their milieu - rather than just one aspect such as mode choice or amount spent.

Classification of shopping activity into a finite number of bundles is done using a polythetic divisive strategy. The implementation adopted here is virtually identical to that discussed in chapter 3. A couple of minor modifications are necessary:

(a) To suppress aspects of the shopping trip which might directly correlate with exogenous variables the range of attributes is reduced. Neither mode of travel nor previous activity are included in the list of attributes. Consequently the classification is less comprehensive.

(b) Previously principal trips were classified for each week and results from separate weeks were compared. This approach is suitable for an assessment of replication, it is less helpful in the construction of a repeat-activity matrix. Instead, all principal trips within an observation period are grouped simultaneously. Over a 4 week period, 3 principal trips by an individual might be allocated to bundle 1 and 1 trip to bundle 2.

No other significant changes are made.

Throughout the discussion of zero-order activity models only results from the polythetic divisive strategy are mentioned. Experimentation with other methods has been undertaken. K-means clustering was used in one study to compare occupancy of 5 bundles by working and non-working women (Uncles 1984c). While paid employment was a crucial influence on women's behaviour, much unexplained heterogeneity was detected. Apparently, working women attempt to minimise time spent on family maintenance activities (ie. their major shopping is highly concentrated) but they still engage in supplementary 'topping-up' trips during lunchtimes and on return journeys from the workplace. Many results remain consistent irrespective of which technique is adopted.

Example 3 A Dichotomous Model: Form of Activity on Principal Trips

Attributes which might correlate strongly with exogenous variables are masked from the classification process. Thus, mode of travel, age of shopper, working status and size of household are all suppressed. Of the attributes which remain two are numeric (expenditure and number of goods bought), three are qualitative (dummies for early evening shopping, multi-stage shopping and the purchase of bulky non-perishable goods), six disordered multi-states are included (subsequent and previous activities, day and product groups, types of shop and home locations), finally a single ordered multi-state is defined (time of trip).

With this set of attributes the distinctive nature of principal trips is investigated. For a sample of 293 Cardiff consumers the attributes associated with principal trips each week are recorded. The observation period lasts 4 weeks (ie. n=4); this period is long enough to give meaningful results without proving unmanageable or unestimable. A repeat-activity matrix is constructed when individuals are classified into similar bundles over the 4 successive weeks.

In the dichotomous case attributes are used to classify principal trips into two activity bundles. Activity bundle 1 captures multi-stage daytime shopping, while activity bundle 2 defines single-stage shopping trips, many of which occur during the early evening. Among the whole sample 45% of trips are allocated to bundle 1 and 55% to bundle 2.

Characteristics of these bundles are described in detail:

(a) Bundle 1 (multi-stage trips)

About 90% of trips occur during the working day, especially Friday and Saturday, and over 80% are multi-stage. Moderate amounts of expenditure and purchasing are observed: a mean of £10 per principal trip is spent on 7-16 product fields. Invariably the trip starts from home and is destined for district centres in Cardiff. A negligible number are destined for isolated shops and originate from workplaces.

(b) Bundle 2 (single-stage trips)

By contrast, 92% of trips in bundle 2 are single-stage. Large numbers take place early in the evening on Thursday and Friday, and there are proportionately fewer trips during mornings.

Table 2.6

Maximum Likelihood Estimates for a Dichotomous Model of Shopping Activity

Variable	Parameter estimates $\underset{\sim}{\alpha}$	$\underset{\sim}{\beta}$	Partial effect	Likelihood ratio test	Significance level
Constants	-1.36 (2.6)	-1.57 (2.8)			
Income	0.27 (1.9)	0.24 (1.7)	0.01	4	80 %
Size	0.05 (0.5)	0.11 (0.9)	-0.02	1	-
Deep freezer	-0.33 (0.9)	-0.54 (1.5)	0.05	3	75 %
Working status	0.83 (2.4)	1.01 (2.9)	-0.04	8	98 %
Driving licence	-0.13 (0.3)	0.11 (0.3)	-0.06	1	-
Once a week	0.11 (0.9)	-0.28 (1.1)	0.10	14	99 %

Sample of travelling consumers 293
Asymptotic t values in parentheses
Partial effects defined from $(\alpha-\beta)m(1-m)$, where
m = mean predicted probability of activity bundle 1
Likelihood ratio test distributed as χ^2 with
2 degrees of freedom

Typically the journey starts and ends at home. Often shops patronised are in district centres, though a significant number are free-standing superstores outside the central area of Cardiff. Expenditure on these occasions is around £18, which is allocated to about 18 product fields.

A beta-logistic model with six exogenous variables was fitted to these activity bundles. Table 2.6 lists the variables, together with parameter estimates. The α parameters relate to activity bundle 1 and the β parameters relate to bundle 2. Income contributes significantly to the model but it is not an effective discriminator between bundles. Larger households have a higher propensity to be characterised by bundle 2 type trips (ie. single-stage) and the influence is especially important beyond the average size category (ie. for the 26% who live in 4-member households). The 65% of shoppers who hold a current driving licence are less likely to be in the multi-stage bundle: many use a car for shopping and are attracted to isolated superstores or single precincts.

Finally, the variable 'once a week' is a measure of consumer attitudes. Shoppers were asked whether they agreed with the statement: 'I would prefer to do all my shopping just once a week'. Some 47% of the sample stated that they prefer to shop just once a week. This response is associated with consumers who reveal behaviour that is typical of bundle 1.

Significance tests (in the final three columns of table 2.6) show how size and driving licence contribute little. Whereas the desire to shop once a week is highly significant, so too is the working status of each person. These variables are revealing the effect of available time: those who work have little time for family maintenance, must be more efficient in their budgeting and scheduling of activity, and have a wider choice of retail outlets. Income and deep freezer ownership are almost significant.

2.3.1 Heterogeneity

Contrasts between three household types illustrate the discussion of heterogeneity. Type 1 is a low-income single person who wishes to shop only once a week, perhaps because of infirmity. Type 2 lies at the other extreme, a wealthy family of 3 members, the shopper works and holds a driving licence, and because of time constraints would prefer to shop once a week. Finally, type 3 is a large household with moderate income, family maintenance duties are heavy and the shopper does not (or cannot) work.

Despite different attitudes to shopping and the variety of household circumstances all three types are more likely to be characterised by bundle 1 type trips (ie. multi-stage) than by the alternative bundle. The mean probability of selecting activity bundle 1 is 0.66 for those consumers in households 1 and 2, this probability falls to 0.57 in the large family (see table 2.7). Higher moments reveal a greater variety of forms than one might expect from mean probabilities. The largest family has a mode at 1 (multi-stage shopping is more likely), whereas the single-person has a bimodal distribution of choice probabilities and a high variance of 0.14.

Table 2.7

Characteristics of the Mixing Distribution for a Dichotomous Model of Shopping Activity

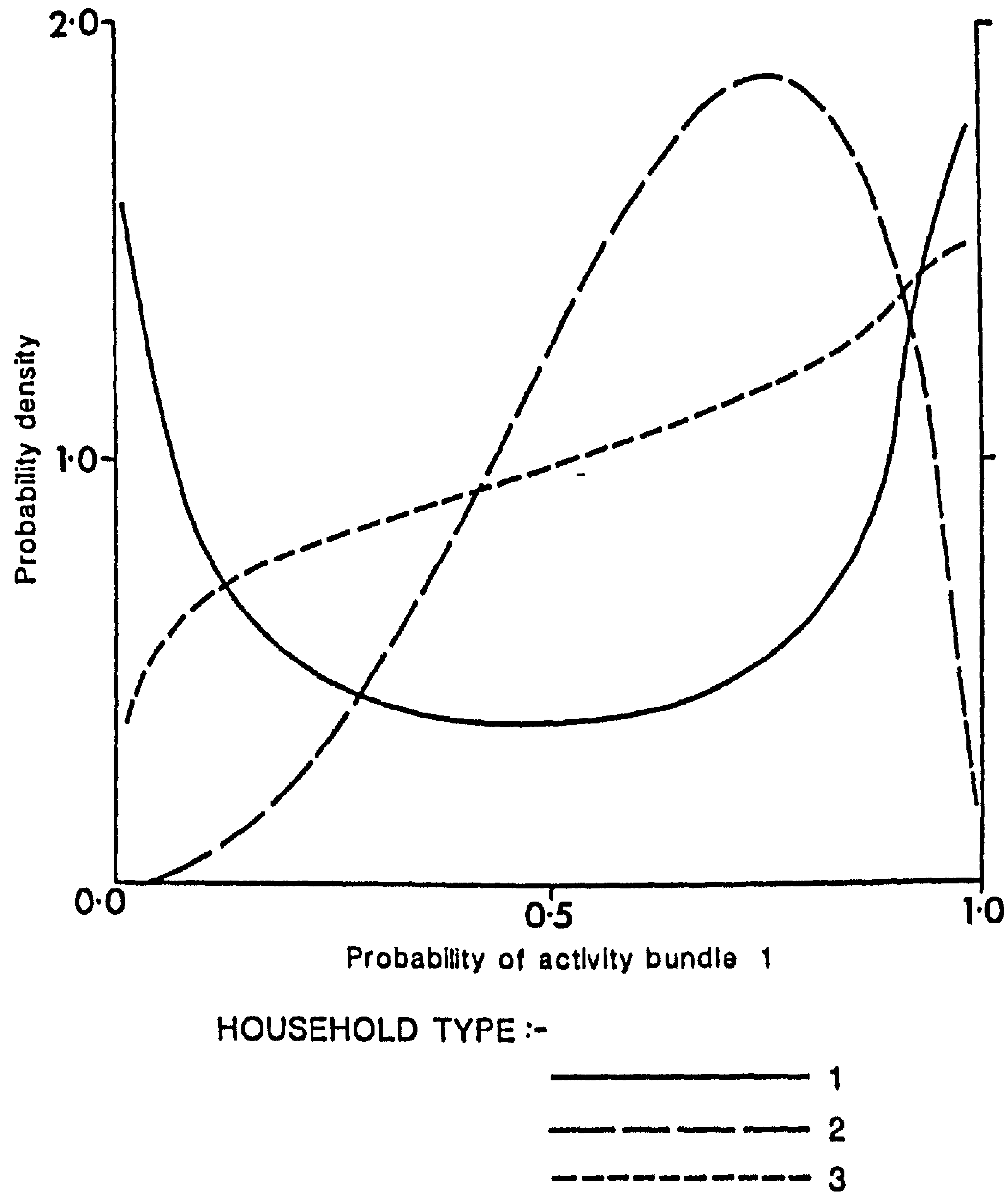
Household type	a_i	b_i	Mean(p_i)	Mode(p_i)	Var(p_i)
1	0.38	0.20	0.66	bimodal	0.14
2	3.19	1.68	0.66	0.76	0.04
3	1.20	0.89	0.57	1	0.08

Definition of Household Types

Type	Income	Size	Deep freezer	Working	Driving licence	Once a week
1	low	single	no	no	no	yes
2	high	nuclear	yes	yes	yes	yes
3	moderate	large	yes	no	no	no

Figure 2.7

MIXING DISTRIBUTIONS FOR DIFFERENT HOUSEHOLD TYPES IN THE DICHOTOMOUS ACTIVITY MODEL



Most interesting are the 'shapes' of mixing distributions (figure 2.7). All a_i values exceed b_i values so the negative skew is a common feature. The single-person household (type 1) describes a characteristic U shape, the large household (type 3) has a J shape, and the wealthy household (type 2) describes a single mode at 0.76 and has a humpbacked distribution around the mode. In substantive terms the large household (type 3) will nearly always be associated with multi-stage trips, whereas single-persons (type 1) will exhibit behaviour that is far more variable.

Example 4 A Polychotomous Model: Forms of Activity on Principal Trips

Just as it is possible to extend the basic beta-logistic model to handle multi-choice problems, so the model can be extended to treat multiple activity-bundles.

Attributes used in polythetic classification are the same as those in example 3: two are numeric, three are qualitative, six are disordered multi-states and there is a single ordered multi-state. All socio-economic attributes were masked from the process of classification. Analysis again is confined to principal trips recorded by 293 consumers in Cardiff over 4 weeks.

A four-alternative model is developed.

(a) Bundle 1

The first activity bundle, to which 45% of the sample are allocated, is equivalent to bundle 1 in the previous example. Shopping is multi-staged, occurs mainly during the daytime and involves moderate levels of expenditure and buying.

(b) Bundle 2

Activity bundle 2 represents 22% of the sample, it is distinguished by single-stage trips during mid-day and afternoon, expenditure of about £20 is quite high and typically over 20 goods are bought. The early morning period, before 10 am, is relatively under-represented. Friday shopping is exceptionally important and most trips terminate at home.

(c) Bundle 3

The next bundle, type 3, is also dominated by single-stage daytime trips, but expenditure is low (no more than £6 is spent on roughly 5 product fields). Of all the bundles, type 3 is the most evenly spread across days of the week.

(d) Bundle 4

Finally, type 4 is a bundle of trips which almost wholly take place early in the evening, especially on Thursday and Friday. The group shuns mornings. Most trips are one staged, starting from home or workplace and returning home. Shops and superstores

Table 2.8

Maximum Likelihood Estimates for a Polychotomous Model of Shopping Activity

Variable	Parameter estimates $\underset{\sim}{\alpha}_1$	$\underset{\sim}{\alpha}_2$	$\underset{\sim}{\alpha}_3$	$\underset{\sim}{\alpha}_4$	Likelihood ratio test	Signf. level
Constants	-1.15 (3.0)	-2.56 (6.4)	-1.94 (4.3)	-2.23 (5.5)		
Income	0.32 (3.0)	0.42 (3.8)	0.11 (0.9)	0.28 (2.5)	19	99 %
Working status	0.55 (1.9)	0.50 (1.7)	0.68 (2.2)	0.84 (3.0)	9	90 %
Driving licence	-0.36 (1.1)	-0.47 (1.5)	0.16 (0.5)	-0.11 (0.3)	6	75 %
Once a week	-0.27 (1.0)	0.57 (2.1)	0.02 (0.1)	0.35 (1.3)	20	99 %

α_1 to α_2 relate to bundles 1 to 4

Sample of consumers 293
Asymptotic t values in parentheses
Likelihood ratio test distributed as χ^2 with
4 degrees of freedom

outside Cardiff city make an important contribution. High to moderate amounts of spending are recorded (£19 on about 15 product fields). Almost 20% of the sample have trips in bundle 4.

A set of four variables is defined. Household income is a 7 category ordinal measure, working status and possession of a driving licence are binary variables associated with the shopper, and 'once a week' is an attitudinal measure. Given that there are 4 bundles and 4 exogenous variables the number of Dirichlet parameters is 20 (including constants), and these are estimated by the method of maximum likelihood. The complete set of parameter estimates is shown in columns 1 to 4 of table 2.8 and below each is the asymptotic t value.

Rising income increases the likelihood of shopping mid-day or during the afternoon, especially on Friday, and has a greater effect on heavy purchasing than on light purchasing. As expected, the working status of shoppers is most closely associated with bundle 4: to participate in paid employment means that single-stage shopping during the early evening at superstores and free-standing stores is more likely.

Possession of a driving licence discourages multi-stage trips and tends to give shoppers a certain freedom of movement: many trips occur during the morning and early in the week. Trips at these times are combined with other aspects of family maintenance (childcare, personal business, etc). Finally, a preference for shopping just once a week is articulated among those who currently make single-stage trips: revealed behaviour and expressed preference are both pointing in the same direction of less complex trip-making.

A likelihood ratio test, distributed as χ^2 with 4 degrees of freedom, indicates the significance of each variable. Highly significant (at 99%) are measures of income and attitude, while the dummy for driving licence is least significant.

2.3.2 Heterogeneity

Now that the number of alternative activity bundles is 4, only two household types are given to illustrate the effect of heterogeneity. A household with average income is defined, the shopper does not work but a driving licence is held. Household type 2 is very different; income is high, the shopper works and holds a driving licence, expressed too is a preference for shopping just once a week.

Mean probabilies are generally low. For three of the activity bundles which are available to household 1, the mean probability is below 0.20. Bundle 1 - multi-stage shopping - is most likely to be occupied. The high income group, household 2, reveals a lower probability of participating in multi-stage shopping (mean p_{12} = 0.33) and shuns mornings early in the week (mean p_{32} = 0.09). These features of the Dirichlet-multinomial mixing distribution are presented in table 2.9 and figures 2.8 and 2.9.

Table 2.9

Characteristics of the Mixing Distribution for a Polychotomous Model of Shopping Activity

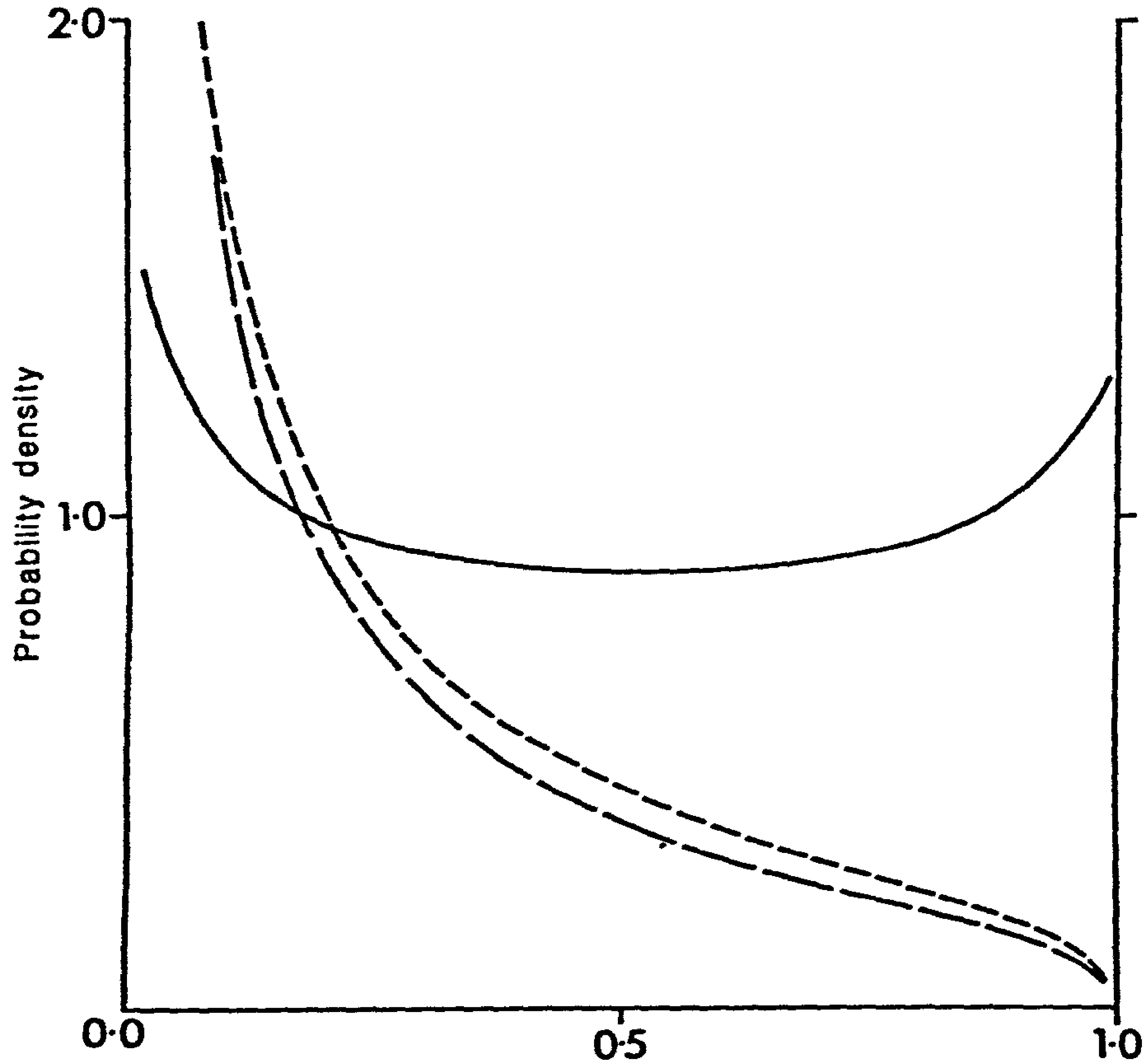
Type	a_{ji}	$S_i - a_{ji}$	Mean(p_{ji})	Mode(p_{ji})	Var(p_{ji})
Household $i = 1$					
j = bundle 1	0.79	0.82	0.49	bimodal	0.10
j = bundle 2	0.26	1.35	0.16	bimodal	0.05
j = bundle 3	0.26	1.35	0.16	bimodal	0.05
j = bundle 4	0.30	1.31	0.19	bimodal	0.06
Household $i = 2$					
j = bundle 1	2.75	5.64	0.33	0.27	0.02
j = bundle 2	2.66	5.73	0.32	0.26	0.02
j = bundle 3	0.73	7.66	0.09	0	0.01
j = bundle 4	2.25	6.14	0.27	0.20	0.02

Definition of Household Types

Type	Income	Working	Driving licence	Once a week
1	low-moderate	no	yes	no
2	high	yes	yes	yes

Figure 2.8

MIXING DISTRIBUTIONS FOR HOUSEHOLD i=1 IN THE POLYCHOTOMOUS ACTIVITY MODEL

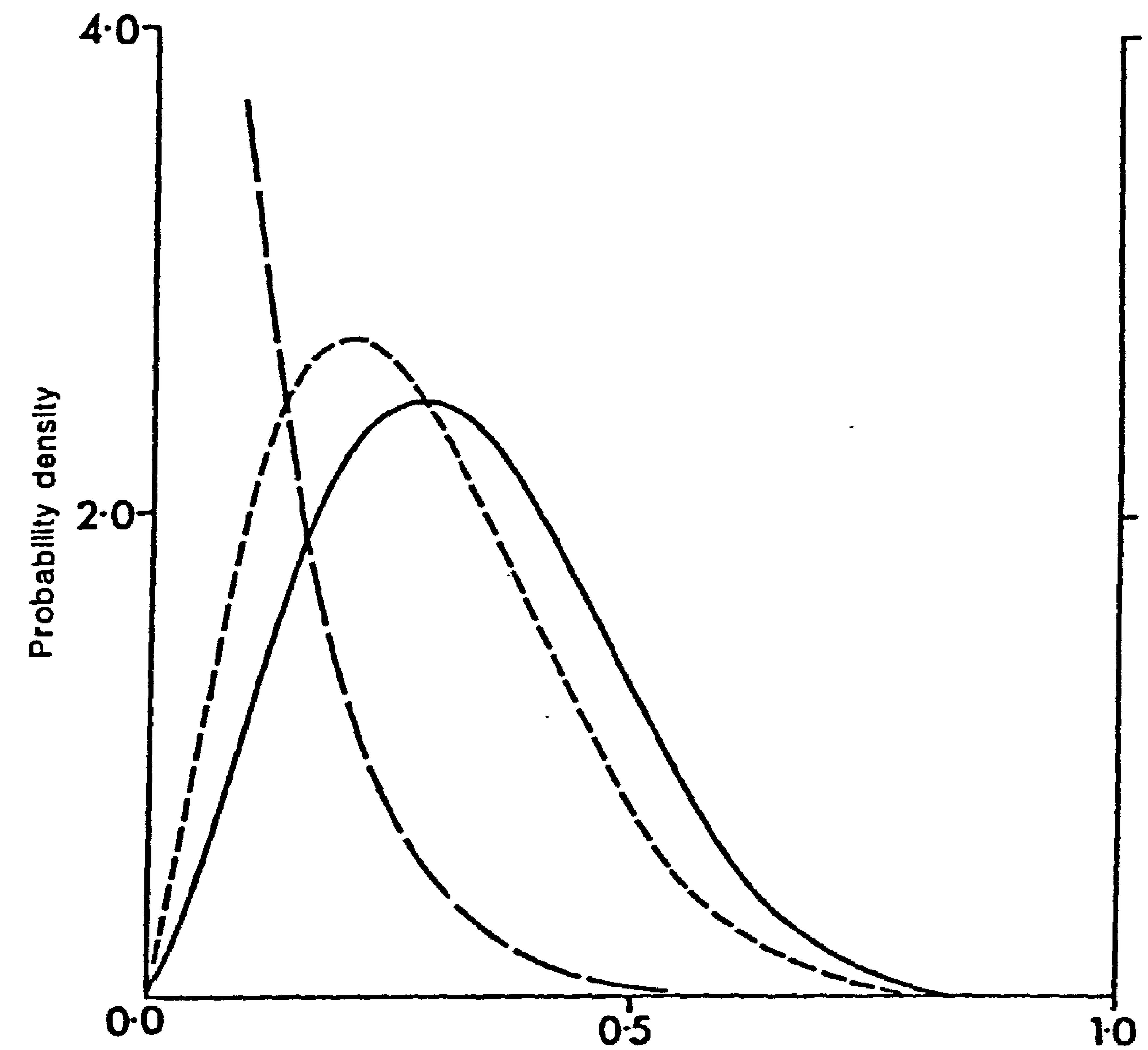


ACTIVITY BUNDLES :-

——— j=bundle 1
— — — { j=bundle 2, j=bundle 3 }
- - - - j=bundle 4

Figure 2.9

MIXING DISTRIBUTIONS FOR HOUSEHOLD i=2 IN THE POLYCHOTOMOUS ACTIVITY MODEL



ACTIVITY BUNDLES :-

——— { j=bundle 1, j=bundle 2 }
— — — j=bundle 3
- - - - j=bundle 4

In terms of higher moments there is an interesting difference between the two households. All mixing distributions for the first household are bimodal with characteristic U shapes, whereas for household 2 distributions are unimodal and mainly humpbacked. Positive skews are observed, and bundle 3 in household 2 is even associated with a mode at 0.

Taken collectively, heterogeneity is greatest when the mean is high and least when the mean is low. Therefore, as the probability of occupying a particular state rises the amount of variation will increase. These trends in the level of heterogeneity point to the presence of unobserved random variation and omitted variables.

Perhaps it is not too surprising that the effective delineation of complex behaviour requires that more than a few simple life-style factors are considered, and that subliminal variations in tastes and motivations will always have an important random influence.

3 Goodness of Fit and Intertemporal Dependence

3.1 Assessment of Trip Models

The need to assess goodness of fit, model diagnostics and functional form is a theme that runs throughout multivariate and time-series statistics. This was recognised in earlier chapters when attention focussed on diagnostic tests, model stability and sensitivity. Only in recent years have techniques become available for the assessment of models that work with countable and quantal responses. Even less developed are suitable techniques for models that work with panel data.

Conventional tests for the correctness of models are based upon an examination of regression residuals. In the case of logistic and poisson models it is the close affinity between least squares residuals and maximum likelihood 'residuals' that makes diagnostic testing possible. Equivalent 'residuals' in panel data models are not immediately available.

Chesher and Irish (1984) derive 'residual-like' expressions which assist in the appraisal of quantal and censored models (mainly probit and tobit). Their approach is entirely consistent with earlier tests for binary data. Also, ad hoc procedures have been developed in market research and event history analysis (Massy et al. 1970, Davies et al. 1982).

In the next couple of sections the correctness of models and the possibility of intertemporal dependence are examined for the beta-logistic model. While these issues - model specification and intertemporal dependence - appear to be distinct there are important links which will be emphasised. The examination closely follows the work of Heckman and Willis (1977) and Heckman (1981b). Here we note that a crucial step is the derivation of predicted probabilies (sections 3.1.1 and 3.2.1). While Heckman does not explicitly link beta-logistic predicted probabilities with Pregibon's 'residuals' the analogy could be helpful.

An important by-product is the calculation of mean predicted probabilities, these enable us to examine the zero-order assumption (sections 3.1.2 and 3.2.2). If the zero-order assumption is violated a more complex model is required, one that takes into account intertemporal dependence or feedback effects. Otherwise we achieve enormous economy by selecting a well-specified parsimonious model, such as the zero-order beta-logistic model.

The results presented here show that the beta-logistic model of travel and activity performs well: the fit is good and intertemporal dependence is not a problem. Heterogeneity due to omitted variables, rather than random variation, is a more important area of concern and remains to be investigated further. While the Dirichlet-logistic model is not subject to the same analysis it is not difficult to obtain predicted probabilities and there is no reason to suppose that performance is markedly worse.

Example 5 A Dichotomous Model: Mode Choice on Principal Trips

Use is made of a simplified model of mode choice. In order to make the principal shopping trip each week, shoppers in the city of Cardiff are assumed to face a two-alternative choice set: either they use a car or another mode is chosen such as walking or local bus. The sample comprises 293 individuals whose mode choices are observed over 5 weeks. All these individuals kept a complete record for 5 weeks; this period of observation is regarded as long enough to provide informative results without making presentation too unmanageable. Other details are similar to those adduced in section 2.1.

Four exogenous variables are included: income and size (both ordinal measures), and two binary dummy variables denoting work status and deep freezer ownership. The justification for this selection of variables was stated earlier. Since the observation period is short the possibility of time-varying exogenous variables does not arise, though in a medium-term transport analysis the profile of household wealth and life-style would alter and affect patterns of movement.

Parameters α and β of the beta-logistic model are estimated for the 4 variables by maximum likelihood methods. These parameter estimates are shown in the first two columns of table 3.1, where α refers to car-choice and β refers to other travel modes. Below each parameter estimate is the asymptotic t value; at conventional significance levels ($t > 1.9$) most parameter estimates are acceptable.

Prior expectations tend to be borne out. Thus, higher income raises the probability of travelling by car to undertake principal weekly shopping and, conversely, reduces the probability that local bus services are patronised or that the shopper chooses to walk. Only the contribution of deep freezer ownership appears to be dubious, and even here the signs accord with expectations. There is a propensity for owners of deep freezers to choose car travel, presumably because this mode alone offers a convenient way to transport bulky goods.

Shown in the next three columns of table 3.1 are the results of tests to assess the contribution of each variable. Partial effects, calculated from parameter estimates and mean predicted probabilities (defined in example 1), reveal large positive contributions from income and deep freezer variables. Participation in employment does raise the propensity to choose a car, but the effect is less influential. Increasing household size deters car usage.

A further test compares likelihood statistics. Each variable is removed in turn from the full model, this gives a set of 8-parameter models and a set of likelihood statistics. The likelihood ratio between the full model and every 8-parameter model provides test statistics distributed as χ^2 with 2 degrees of freedom (one degree for each parameter removed). By this method, household income, size and deep freezer ownership prove to be significant. Less convincing is the likelihood ratio for working status (it is significant at 85%). It is

Table 3.1

Maximum Likelihood Estimates for a Dichotomous Model of Mode Choice

Variable	Parameter estimates $\underset{\sim}{\alpha}$	$\underset{\sim}{\beta}$	Partial effect	Likelihood ratio test	Significance level
Constants	-1.92 (3.7)	0.33 (0.6)			
Income	0.35 (3.4)	-0.16 (1.5)	0.13	55	99 %
Size	-0.20 (2.1)	-0.11 (1.1)	-0.02	5	90 %
Deep freezer	0.16 (0.6)	-0.26 (1.0)	0.10	5	90 %
Working status	0.58 (2.0)	0.37 (1.3)	0.05	4	85 %

Sample of travelling consumers 293
Asymptotic t values in parentheses
Partial effect defined from $(\alpha-\beta)m(1-m)$, where m is the mean predicted probability of car travel
Likelihood ratio test distributed as χ^2 with 2 degrees of freedom

Table 3.2

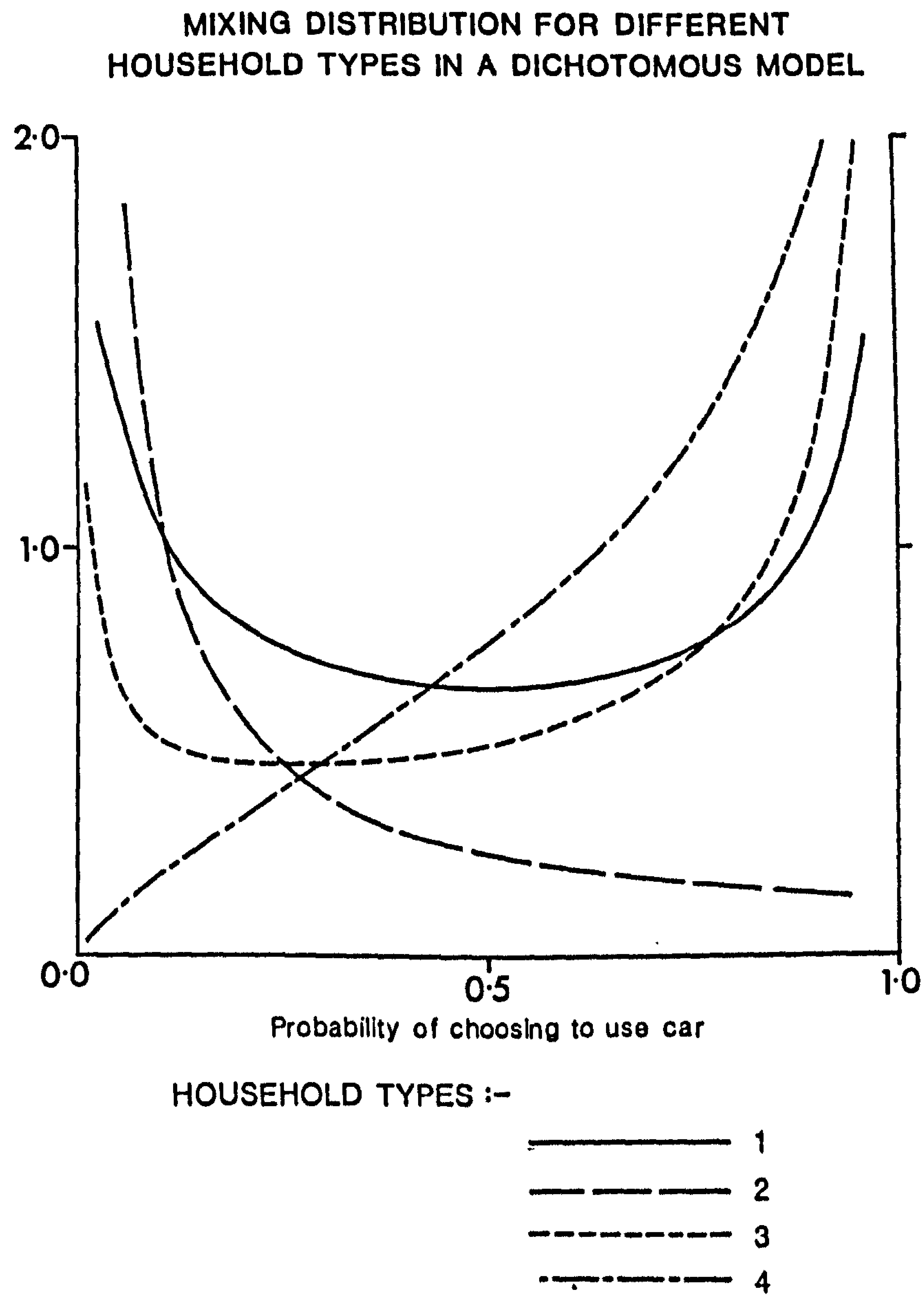
Characteristics of the Mixing Distribution for a Dichotomous Model of Mode Choice

Household type	a_i	b_i	Mean(p_i)	Mode(p_i)	Var(p_i)
1	0.56	0.53	0.51	bimodal	0.12
2	0.14	0.95	0.13	bimodal	0.05
3	0.76	0.31	0.71	bimodal	0.10
4	1.75	0.69	0.72	1	0.06

Definition of Household Types

Type	Income	Size	Deep freezer	Working
1	average	average	yes	yes
2	low	low	no	no
3	high	high	yes	yes
4	high	low	no	yes

Figure 3.1


MIXING DISTRIBUTION FOR DIFFERENT
HOUSEHOLD TYPES IN A DICHOTOMOUS MODEL
2·0
1·0
0·0
0·5
1·0
Probability of choosing to use car
HOUSEHOLD TYPES :-
1
2
3
4

worthwhile to retain all these variables.

The characteristics of travel choice and the mixing distributions are calculated for 4 household types. Type 1 is a middle income household in which the shopper works. Type 2 is a young couple with low income. Members of both final groups are affluent and working, one living within a large family, the other living alone. Aspects of the mixing distributions for these types are described in table 3.2 and are plotted in figure 3.1. All figures are derived in a manner similar to that discussed in section 2.1.

Among low income couples (type 2) the mean probability of choosing to travel by car is merely 0.13, whereas this probability rises to over 0.70 for high income families whose members are engaged in work (types 3 and 4). There is considerable variation between sub-groups of the Cardiff panel, and a sharp contrast is drawn between high income and low income consumers in their propensities to travel by car when they shop.

Within sub-groups there is evidence of further variation. Associated with households 1 and 3 are bimodal beta distributions and large variances of 0.12 and 0.10 (see the final two columns of table 3.2 and the plots in figure 3.1). Evidently members of households 1 and 3 nearly always, or hardly ever, choose a car to reach their destination and few consumers will alternate between these extremes.

Members of household type 4, the rich small families, almost always drive to shops. Not surprisingly, type 2 consumers, whose income is low, tend to go by foot or bus.

Clear evidence of heterogeneity is found in these examples. Some of the heterogeneity may be due to omitted variables rather than purely random variations in taste. The U shaped mixing distributions for households 1 and 3 might arise from factors which favour shopping by foot and because good shopping outlets can be found nearby. A measure of proximity to good shopping facilities might improve the model.

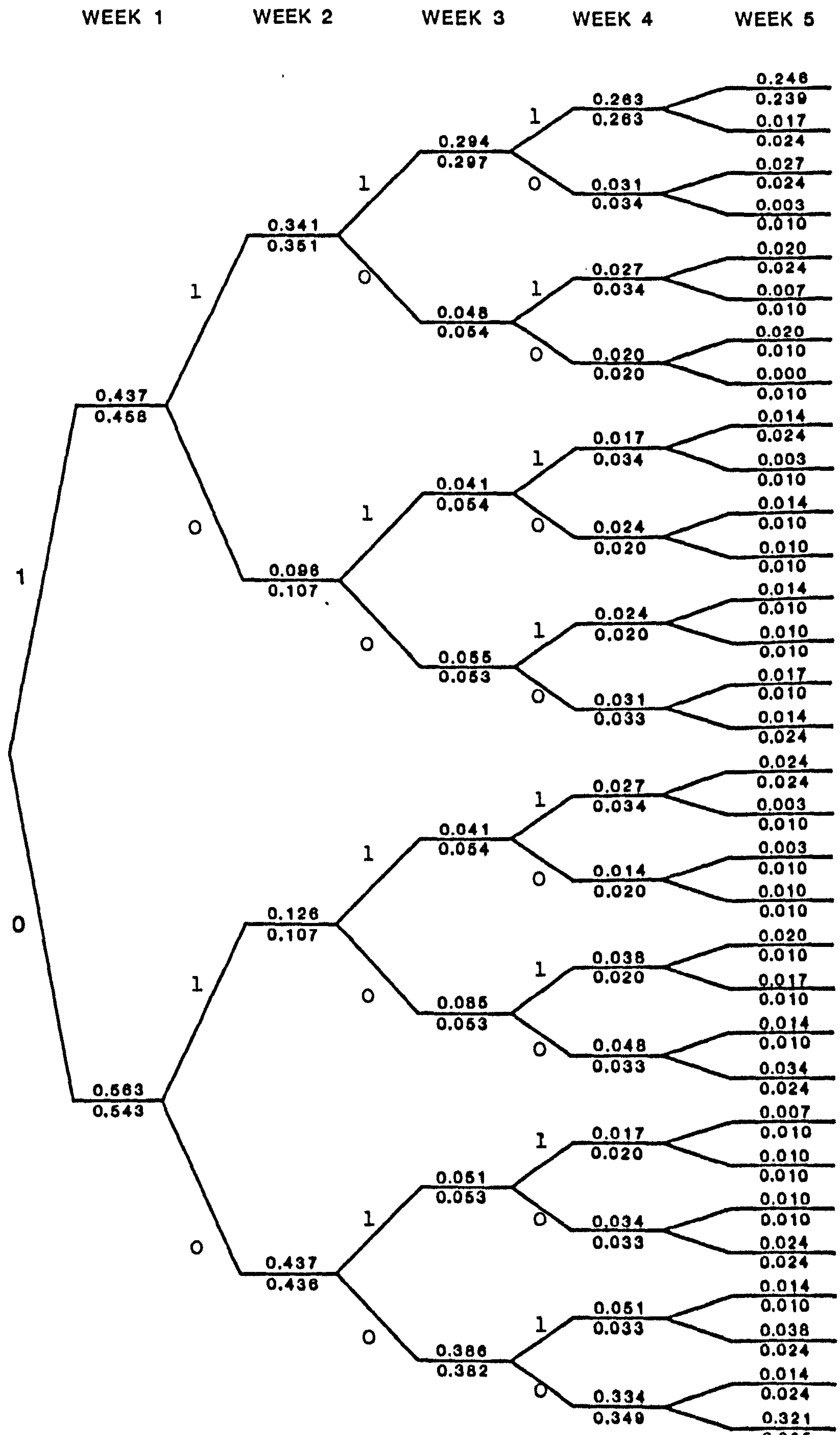
So far the higher moments of the beta-logistic model have been used to emphasise heterogeneity. Now attention is turned to two further aspects of model assessment: (a) goodness of fit, and (b) intertemporal dependence. To examine these issues 'residual-like' values are calculated.

3.1.1 Goodness of Fit

To assess the fit of the model, observed proportions travelling by car are compared against mean predicted probabilities. This is done for 5 weeks and for each branch of the binary split into car/no car. In figure 3.2 the result is presented as a 'binomial tree' (following Heckman and Willis 1977). Actual proportions are placed on top of each branch, and mean predicted probabilities below. For example, in the first week 44% of shoppers choose to travel by car (these follow the '1' branch) compared with 56% who select some other means (these follow the '0'branch). Paths can be traced over several time periods, for example 25% always travel by car.

Figure 3.2

ACTUAL AND PREDICTED CAR CHOICE PROBABILITIES, PATHS OVER 5 WEEKS



1 Proportion choosing to travel by car

0 Proportion choosing not to travel by car

Actual proportion (top). Predicted proportion (bottom)

The mean values shown in figure 3.2 are obtained from individual probabilities which are 'residual-like'. The mean predicted probability for individual i, who chooses car in $j = 0,1,\ldots,n$ weeks and does not choose car in $k = n-j$ weeks, is evaluated within the expression:

$$p_i = \frac{B(a_i+j, b_i+k)}{B(a_i, b_i)}$$

where $B(.)$ = beta function

$a_i = e^{\underset{\sim}{x}_i'\underset{\sim}{\alpha}}$ and $b_i = e^{\underset{\sim}{x}_i'\underset{\sim}{\beta}}$

$\underset{\sim}{x}_i'$ = vector of exogenous variables for i^{th} person

Alternatively the computational formula is used:

$$p_i = \frac{\Gamma(a_i+j) \quad \Gamma(b_i+k) \;/\; \Gamma(a_i+b_i+j+k)}{\Gamma(a_i) \quad \Gamma(b_i) \;/\; \Gamma(a_i+b_i)}$$

where $\Gamma(.)$ is the gamma function and all other terms are defined above.

To obtain mean predicted probabilities for the whole sample we sum over i:

$$\text{mean}\left[p(j,n)\right] = \sum_{i=1}^{N} p_i(j,n) \;/\; N$$

where $p(j,n)$ is the probability of choosing car j out of n weeks.

As an example consider the choice of car in the first week. The mean predicted probability of choosing to travel by car is 46%. Similarly, continuous use of the car over the first two weeks is predicted to be 35%.

Overall, correspondence between actual and predicted values is very good. Departures amount to only a few percentage points, such as the 2% over-prediction of car choices in week 1. Differences of only a couple of percent represent no more than 6 consumers from a total sample of 293.

Construction of the binomial tree is a crucial step, we now have the data to assess a number of the questions posed earlier.

Special interest often centres around continuous choice probabilities, ie. where a person or sub-group always select a particular mode, a particular route, or a particular store in which to buy weekly provisions. Continuous probabilities are given in table 3.3. Even after five weeks the probability of continuously selecting the same mode as in the first week remains high: there is a 24% predicted probability of selecting car travel in week 5, after four previous weeks in which the car has been chosen.

Table 3.3

Probabilities of Continuous Choice of Car Travel and Non - Car Travel

	Week t				
	1	2	3	4	5
Probability of choosing car travel until week t:					
Actual	.44	.34	.29	.26	.25
Predicted	.46	.35	.30	.26	.24
Probability of not choosing car travel until week t:					
Actual	.56	.44	.39	.33	.32
Predicted	.54	.44	.38	.35	.33

Table 3.4

Actual and Predicted Distribution of Weeks with Car Travel from Week 1 to Week 5

Weeks with Car Travel	Percent of Sample		Discrepancy (percentage points)
	Actual	Predicted	
5	25	24	0.7
4	10	12	1.8
3	9	10	0.6
2	11	10	1.2
1	12	12	0.4
0	32	33	0.4
	100	100	

Two aspects are really important:

(a) Car choice is different from many other choices. Other elements of the shopping trip, such as store choice, product choice and brand selection, exhibit less loyalty and some switching of allegiance between competing alternatives.

(b) The discrepancy between observed proportions of continuous choice and predicted probabilities is slight. For the two series shown in table 3.3 the average differences are merely 0.8% and 0.9% spread over 5 weeks.

An alternative presentation of these results is provided by table 3.4. Here is shown the distribution of weeks with car travel. For example, the actual number of consumers who travel by car on every principal trip is 25% (24% predicted), the actual number who travel by car for four out of five principal trips is 10% (12% predicted), and so on. Continuous choice paths dominate, while the least likely pattern is to choose car on two or three occasions and another mode on the remaining occasions. Furthermore, it is among the switching choice paths that the difference between actual and predicted values is greatest: discrepancy being 1.8% when the car is chosen on four occasions and 1.2% when car is chosen twice. Again, the main point is that the fit is very good.

3.1.2 Intertemporal Dependence

We now need to establish whether intertemporal dependence has a subtle effect not brought out by the analysis so far. It has been assumed that the stochastic choice process is Bernoulli or zero-order, whereby current choices are independent of previous history and selected probabilities in week t are constant. Given that the examination of deviations between actual and predicted probabilities does not uncover any evidence of systematic bias or model failure the zero-order assumption seems to be reasonable. From comments made in section 1.1, however, we need to check that several effects are not being obscured by a good overall fit.

First, recall the distinction between two forms of intertemporal dependence:

(a) True state dependence

True state dependence arises from the influence of past experience on current and future choices. Dependence is real: there are transition or transaction costs if consumers switch between alternatives; utility functions have to be altered fundamentally if an alternative is to be preferred; and a change means overcoming inelastic demand.

For example, consumers repeatedly travel by bus because they acquire knowledge about fare structures, schedules and stops. Switching to another mode, say metro, is costly because new schedules have to be learnt and preferences re-defined. Most probably consumers will be loyal to their last choice, in this case bus.

Because of these transition costs and inelasticities, choice t will be influenced by previous choice t-1.

(b) Apparent state dependence

Apparent state dependence arises when individuals differ in their propensity to experience an event or select a choice. Where different propensities are correlated over time, previous experience will appear to determine current and future choices. Apparent effects are closely associated with observed and unobserved heterogeneity.

To assess true and apparent state dependence the beta-logistic model is compared to the actual sequence of choices and to results from an alternative generating process (see Heckman and Willis 1977, 48-53). Three stages are involved:

(1) Actual transitions between choices are compared against those predicted by the beta-logistic model.

(2) An alternative generating process is assumed, viz. the homogeneous Markov process. This would provide a good fit if (first-order) true state dependence was the major underlying effect.

(3) Conditional probabilities are calculated from predictions of the beta-logistic model. If conditional probabilities are similar, despite different previous choice histories, true state dependence cannot be inferred.

All these exercises seek to establish whether the major effects are due to heterogeneity or intertemporal dependence. Each exercise approaches the topic from a slightly different angle. The sample is assumed to be homogeneous in the Markov model and only temporal dependence can influence choice. In the conditional models temporal dependence is screened out in order to isolate the influence of sample heterogeneity.

(1) Transitions

We turn, then, to the analysis of transitions between choices. Both observed transitions and those predicted by the beta logistic model are considered. The probability that a consumer who occupied state l in week t is in state m in week t+n is denoted $p_{lm}^{(n)}$. In a dichotomous model there are two possible states each week: '1' indicating car travel and '0' representing choice of another mode. Therefore the number of transition probabilities $p_{lm}^{(n)}$ is four:

$$p^{(n)} = \begin{pmatrix} p_{00}^{(n)} & p_{01}^{(n)} \\ p_{10}^{(n)} & p_{11}^{(n)} \end{pmatrix}$$

This matrix is termed the n-step transition matrix. Note that row probabilities sum to one:

$$p_{00}^{(n)} + p_{01}^{(n)} = p_{10}^{(n)} + p_{11}^{(n)} = 1$$

Only results for $p_{11}^{(n)}$ and $p_{01}^{(n)}$ are discussed, these being especially relevant.

The analysis is illustrated by returning to the dichotomous model of mode choice. Actual n-step choice probabilities and those predicted by the beta-logistic model are shown in rows 1 and 2 of table 3.5. Week 1 is the base week t and t+n is associated with all subsequent weeks in turn.

All transitions t to t+n in line 2 are identical since constancy of $p_{lm}^{(n)}$ is an assumption of the beta-logistic model. The probability of transition from car in week t to car in week t+n is 0.77, and 0.20 for the transition from another mode in week t to car in week t+n. The probability $p_{11}^{(n)}$ greatly exceeds $p_{01}^{(n)}$ which suggests that switching between alternatives is less likely than remaining in the same state. However, such behaviour may arise from either true or apparent state dependence, so these predicted transitions are compared against observed values.

Observed transitions in line 1 oscillate. $P_{11}^{(n)}$ falls in the third and fourth weeks and recovers again in week five. The relative trends between observed and predicted probabilities are assessed by applying two rules:

(a) If $p_{11}^{(n)}$ decreases with n and $p_{01}^{(n)}$ increases with n then the tendency is to overstate apparent state dependence. To guard against such overstatement, true state dependence should be investigated.

(b) If $p_{11}^{(n)}$ increases with n and $p_{01}^{(n)}$ decreases with n then the tendency is to understate apparent state dependence. This effect should be investigated further by looking at heterogeneity in the sample.

Inspection of relative trends hints at the behaviour described in rule (b). But the trend is neither consistent nor marked. The result implies that true state dependence is not something to worry about, and that apparent state dependence should be given closer attention.

Table 3.5

Predicted and Actual n - step Car Choice Probabilities for t = Week 1 and t + n = Week 2, Week 3, Week 4 and Week 5

	Week = t + n			
	Week 2	Week 3	Week 4	Week 5
$p_{11}^{(n)}$				
1. Actual	.78	.77	.76	.85
2. Beta-Logistic	.77	.77	.77	.77
3. Markov	.78	.66	.59	.55
$p_{01}^{(n)}$				
1. Actual	.22	.16	.24	.19
2. Beta-Logistic	.20	.20	.20	.20
3. Markov	.22	.35	.42	.46

Table 3.6

Actual Car Choice Probabilities in Week t for Consumers who have travelled by Car in 1 of the 2 preceding Weeks

Group	Week t			Average
	Week 3	Week 4	Week 5	
A	.43	.49	.52	.48
B	.33	.37	.49	.40

Group A: Consumers who travel by car in week t, conditional on having chosen car travel in week t-2 but not in week t-1

Group B: Consumers who travel by car in week t, conditional on having chosen car travel in week t-1 but not in week t-2

(2) Alternative processes

To test further the relative influence of heterogeneity and state dependence an alternative stochastic process is applied to the data. Now the Bernoulli assumptions of independence and constancy are waived, and occupancy of the previous state is allowed to influence current choice probabilities. A Markov chain is generated from actual n-step choice probabilities and the sample of consumers is assumed to be homogeneous.

Markov transitions are calculated for t = week 1 and t+1 = week 2, to give:

$$M = p^{(1)} = \begin{pmatrix} p_{00}^{(1)} & p_{01}^{(1)} \\ p_{10}^{(1)} & p_{11}^{(1)} \end{pmatrix} = \begin{pmatrix} 0.776 & 0.224 \\ 0.220 & 0.780 \end{pmatrix}$$

Results for each n-step transition are presented along row 3 of table 3.5. These entries provide predictions of the rate of decrease in $p_{11}^{(n)}$ and the rate of increase in $p_{01}^{(n)}$. Rates of decrease / increase rapidly take effect and are consistent with an emphasis on the form of true state dependence meant by last-choice loyal (see rule (a)). <u>But</u>, results are totally inconsistent with empirical observations.

The fit is poor. In week 5 the Markov predicted probability for $p_{11}^{(n)}$ departs from actual proportions by about 30% and for $p_{01}^{(n)}$ the departure is 27%. Such a finding - that the Markov chain offers a very poor fit to actual data - agrees with that found in the marketing literature (Ehrenberg 1965) and sharply diverges from the labour studies reported by Heckman and Willis (1977), Lancaster and Nickle (1980), and Heckman (1981b). These studies of women's labour participation rates and unemployment duration point to the coexistence of heterogeneity and intertemporal dependence. The latter mainly arises from heavy transition costs (ie. costs of search in the labour market, costs of hiring and training personnel).

(3) Conditional probabilities

The final exercise looks at conditional probabilities. Consider two groups of decision-makers: those in group A are consumers who choose to travel by car in week t and in t-2, but not in t-1; while group B comprises those consumers who choose to travel by car in week t and in t-1, but not in t-2.

Thus:

group A = p(car in t| no car in t-1, car in t-2)

group B = p(car in t| car in t-1, no car in t-2)

Heckman and Willis state that a pure heterogeneity model, of a beta-logistic type, predicts that the proportion of consumers in each group remains fixed in future time periods. If, however, there are true state dependencies then choice probabilities in week t will fall among members of group A to a level below those for group B.

Observed probabilities from figure 3.2 are used to calculate the conditional probability of travel by car among members of both groups. Thus 0.43 of consumers in group A choose car travel in week 3, compared to about 0.33 for members of group B (table 3.7). Choice of car in t-1 has a marginally lower influence on current choice probabilities than choice of car in t-2: this is the converse of what we would expect if true state dependence was present.

Choice probabilities in group B remain marginally lower than group A for the next two weeks. If we take the average over all three weeks, the difference between both groups is about 8 percentage points. While this difference is not large (indeed there is a tendency for probabilities to converge) choice of car in t-2 has a greater effect than a similar choice in t-1. Certainly this outcome is not indicative of first-order state dependence.

The same two messages are conveyed by all these exercises.

(a) There is much heterogeneity. Omitted variables and random tastes have an important influence on choice. True state dependence is not an important influence.

(b) Mode choice is like many other short-term decisions, for example store and brand selection. All these choices differ from the decision to migrate or to participate in the labour force; in these latter cases true state dependence, feedback and transition costs have a major role. It is important to draw a contrast between spontaneous and fairly inconsequential short-term decisions, and the levels of commitment, investment and complex search involved in long-term decisions. Only the latter will lead to cumulative inertia and a reluctance to change from existing patterns of behaviour.

3.2 Assessment of Activity Models

Two strong conclusions are drawn from the assessment of mode choice models: (a) on average the beta-logistic model fits the data very well, and (b) heterogeneity in the sample is of far greater significance than intertemporal dependence. Now we need to establish whether these findings will generalise.

A variety of mode choice models, estimated on data for 4 and 5 weeks, have been fitted and in every case the message is similar (Uncles 1985). Rather than reproduce these examples, we shall return to the two-bundle model of shopping activity to see if our conclusions are upheld in a different context.

Example 6 A Dichotomous Model:

Forms of Activity on Principal Trips

A consumer reveals behaviour which is characterised by one of two activity bundles: (1) the principal trip is multi-staged, invariably occurs during the morning and involves moderate expenditure; or (2) the shopping trip is single-staged, with heavy expenditure and often happens early in the evening on Thursday and Friday. These two bundles are groups 1 and 2 respectively of example 3. Occupancy of these bundles is observed over a four week period, to give a repeat-activity matrix.

Carrying on from the analysis of heterogeneity in example 3, an appraisal is made of goodness of fit and intertemporal dependence.

3.2.1 Goodness of Fit

A 'binomial tree' is constructed for 4 weeks (figure 3.3). The observed proportion in each bundle is compared against the mean predicted probability, using the beta-logistic model of example 3. These values are shown on the top and bottom of each binomial branch. About 44% of principal trips are actually in bundle 1 and a similar percentage are predicted by the beta-logistic model to be in this bundle. Similarly, just over 56% of principal trips are actually in bundle 2 and the predicted percentage is virtually identical. Correspondence between actual and predicted values is very good.

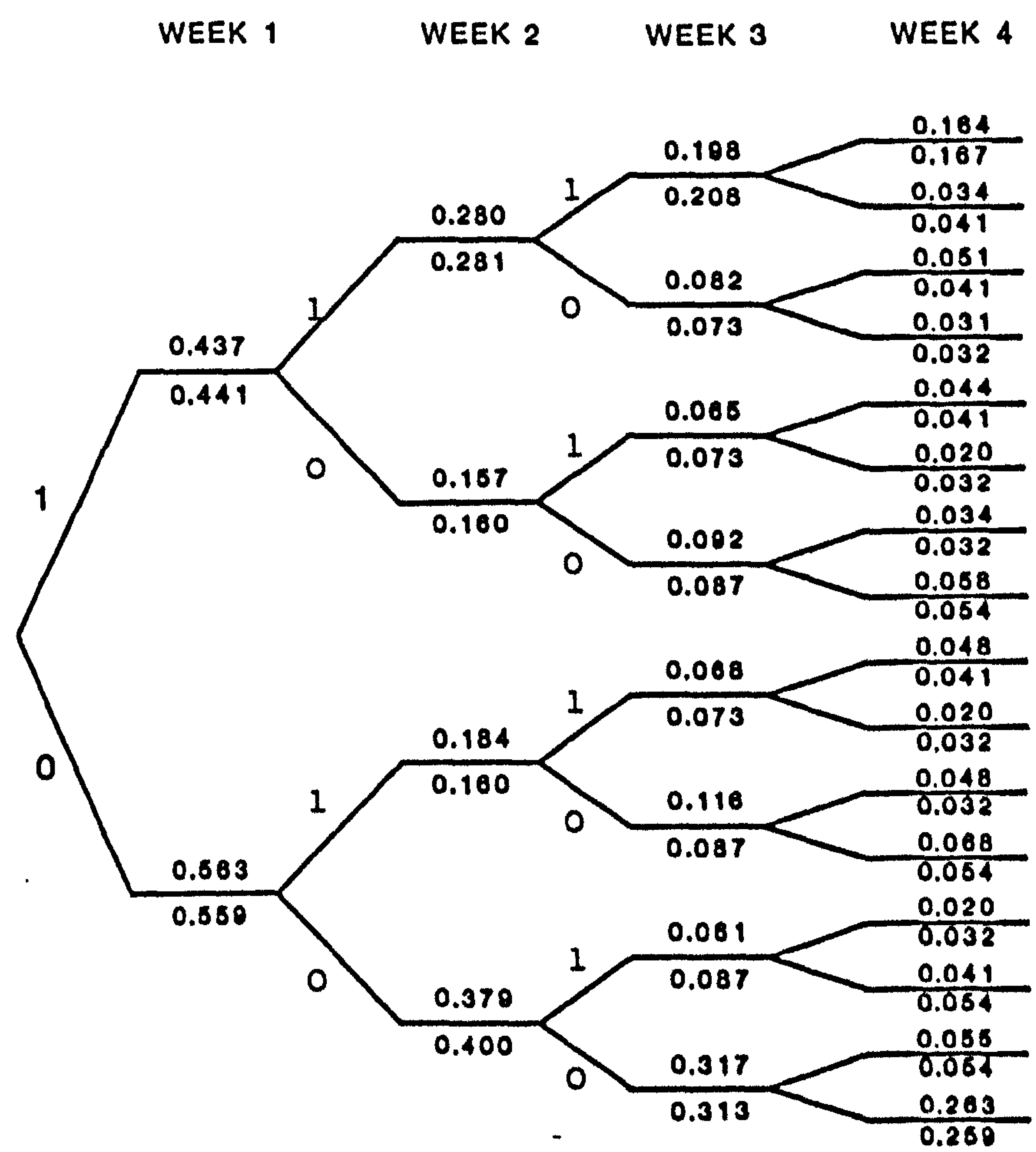
Continuous probabilities are presented in table 3.7. Look at the multi-stage activity bundle (type 1) in rows 1 and 2. Actual and predicted probabilities decline together and the average difference amounts to no more than 1.4%. Likewise, a definite decrease is evident in the alternative activity bundle: in week 1 there is a 56% chance that the principal shopping trip will be single-stage; by week 4 the chance of always having undertaken single-staged trips is down to 26%. The average difference between actual and predicted figures is 0.8%.

Table 3.8 provides an alternative display. The number of weeks in which multi-stage activities occur is expressed as a percentage of the sample. For 16% of the sample bundle 1 characterises trip behaviour in all 4 weeks, this bundle also characterises behaviour in 3 weeks for a further 18% of the sample, and so on. Both actual proportions and predicted probabilities are given, and in the final column discrepancies are calculated.

Discrepancies are low, although where there is a mix of bundles across weeks (ie. switching between patterns of activity) discrepancies rise above 1%. An interesting difference between the distribution of these percentages, compared to those in example 5 (table 3.4), is the dominance of zeros and single entries. Apparently a significant number of shoppers never, or very rarely, reveal a pattern of shopping activity on principal trips that is described by bundle 1 (multi-stage shopping).

Figure 3.3

ACTUAL AND PREDICTED ACTIVITY BUNDLE PROBABILITIES, PATHS OVER 4 WEEKS



1 Proportion following 'multi-stage' activity bundle
0 Proportion following 'single-stage' activity bundle
Actual proportion (top). Predicted proportion (bottom)

Table 3.7

Probabilities of Continuous Choice of Activity Bundles

	Week t			
	1	2	3	4
Probability of choosing multi-stage activity bundle until week t:				
Actual	.44	.28	.20	.16
Predicted	.44	.28	.21	.17
Probability of choosing single-stage activity bundle until week t:				
Actual	.56	.38	.32	.26
Predicted	.56	.40	.31	.26

Table 3.8

Actual and Predicted Distribution of Weeks with Multi-Stage Activity Bundle

Weeks with Multi-Stage Activity Bundle	Percent of Sample		Discrepancy (percentage points)
	Actual	Predicted	
4	16	17	0.3
3	18	16	1.3
2	17	19	1.9
1	22	22	0.6
0	26	26	0.4
	100	100	

Two important observations arise from these results: (a) the beta-logistic model is a good predictor of actual activity, but (b) the fall-off in continuous probabilities implies that repeated occupancy of activity bundles is less likely than repeated choice of car (compare table 3.4). In this respect activity is not like car choice behaviour, instead it shares many similarities with store and brand choice behaviours (as reported by Wrigley and Dunn 1984b).

3.2.2 Intertemporal Dependence

Earlier intertemporal dependence was approached from three angles and these are replicated here. First, the actual transition matrix is compared against the transitions predicted by the beta-logistic model. Next, a comparison is made against results from an alternative generating process. Finally, conditional probabilities are assessed. These approaches are designed to isolate the potential influence of true and apparent state dependence and follow the work of Heckman and Willis (1977) and Heckman (1981b).

(1) Transitions

To recap, the probability that a consumer who occupies state 1 in week t will be in state m in week t+n is written $p_{lm}^{(n)}$. In a dichotomous model there are two possible states each week: '1' indicates occupancy of bundle 1 and '0' occupancy of other bundles. The resultant transition matrix is:

$$p^{(n)} = \begin{pmatrix} p_{00}^{(n)} & p_{01}^{(n)} \\ p_{10}^{(n)} & p_{11}^{(n)} \end{pmatrix}$$

If the stochastic process is truly Bernoulli then each series of transition probabilities from t to t+n will be independent and constant. Actual probabilities may depart from the constant series, so model mis-specification will be revealed as the difference between these two series.

Table 3.9 shows the predicted and actual probabilities for weeks t+n. Given the underlying Bernoulli assumption of the beta-logistic model, all entries along line 2 are equal. The transition probability $p_{11}^{(n)}$ is always 0.64 and the transition $p_{01}^{(n)}$ is always about 0.29. The observation that $p_{11}^{(n)}$ exceeds $p_{01}^{(n)}$ suggests that sample heterogeneity is important (which we know to be true already).

Actual probabilities depart from the 0.64 and 0.29 norms in an unsystematic manner. Actual $p_{11}^{(n)}$ starts to decrease with n, but then recovers; whilst actual $p_{01}^{(n)}$ falls slightly and rises again. From these oscillations it is not possible to say that the beta-logistic model is overstating or understating heterogeneity

Table 3.9

Predicted and Actual n - step Activity Choice Probabilities for t = Week 1 and t + n = Week 2, Week 3 and Week 4

		Week = t + n		
		Week 2	Week 3	Week 4
$P_{11}^{(n)}$				
1.	Actual	.64	.60	.67
2.	Beta-Logistic	.64	.64	.64
3.	Markov	.64	.53	.49
$P_{01}^{(n)}$				
1.	Actual	.33	.23	.30
2.	Beta-Logistic	.29	.29	.29
3.	Markov	.33	.43	.47

Table 3.10

Actual Choice Probabilities in Week t for Consumers who choose the Multi-Stage Activity Bundle in 1 of the 2 preceding Weeks

Group	Week t		Average
	Week 3	Week 4	
A	.41	.49	.45
B	.37	.53	.45

Group A: Consumers who follow a multi-stage activity bundle in week t, conditional on having followed this activity pattern in week t-2 but not in week t-1

Group B: Consumers who follow a multi-stage activity bundle in week t, conditional on having followed this activity pattern in week t-1 but not in week t-2 relative to other effects. Probably the beta-logistic model is about right.

(2) Alternative processes

Along line 3 in table 3.9 Markov transition probabilities are shown. Here the Bernoulli assumptions of independence and constancy are waived and occupancy of the previous state is allowed to influence current behaviour. The Markov model postulates that consumers are reluctant to change states and for a while they linger in the same state, but over time the strength of reluctance wanes and a switch becomes more probable. The sample is assumed to be homogeneous and a Markov chain is generated from actual n-step choice probabilities over the period t = week 1 to t+1 = week 2:

$$M = p^{(1)} = \begin{pmatrix} p_{00}^{(1)} & p_{01}^{(1)} \\ p_{10}^{(1)} & p_{11}^{(1)} \end{pmatrix} = \begin{pmatrix} 0.673 & 0.327 \\ 0.359 & 0.641 \end{pmatrix}$$

All subsequent transitions are multiplied by this first-step transition matrix.

As n increases so the probabilities $p_{11}^{(n)}$ and $p_{01}^{(n)}$ tend to converge; repeated selection of bundle 1 becomes less probable, while switching between bundles becomes more probable. These are the effects that we would expect to observe if the only influence on occupancy of activity bundles was first-order state dependence.

From the results it is clear that a homogeneous Markov process does not provide an adequate account of the data. Rates of change in Markov transition probabilities are much greater than those actually observed - a well known symptom of heterogeneity in Markov chains. In week 4 the average discrepancy between actual and Markov transition probabilities is over 17%, which compares with an average discrepancy of less than 3% between actual and beta-logistic transition values.

Findings from the activity model are consistent with the mode choice example and with results from other short-term studies: the Markov chain is a bad approximation to actual data.

(3) Conditional probabilities

A final check on the relative effects of heterogeneity and intertemporal dependence is made using conditional probabilities. Two groups are defined. Forming group A are those consumers who do not select bundle 1 in week t-1, conditional on having followed this activity pattern in t-2. Group B consists of those consumers who occupy bundle 1 in week t-1, conditional on not having done so in t-2. If the only important effect is ascribed to pure heterogeneity then the same proportion of consumers in both groups should select bundle 1 (multi-stage activity denoted MS) in time t. That is:

group A = p(MS in t | not MS in t-1, MS in t-2)

group B = p(MS in t | MS in t-1, not MS in t-2)

Observed probabilities from figure 3.3 are used to calculate conditional values in weeks 3 and 4. Results are set forth in table 3.10. During week 3 both groups have a 0.40 chance (approximately) of occupying bundle 1. Choice of activity bundle 1 in the preceding state t-1 has neither a lower nor a greater influence on current probabilities than occupancy in t-2. Since the proportion of consumers who select bundle 1 is so similar in both groups the only major influence is that of heterogeneity.

By week 4 the chance of selecting bundle 1 rises to 0.49 for members of group A and 0.53 among members of group B. Now the preceding state t-1 has a proportionately greater effect, but the difference between groups is negligible (4% at most).

On average, choice probabilities among members of both groups are identical. Identical probabilities point to the influence of heterogeneity. We conclude, therefore, that it is more important to account for heterogeneity - arising because of real variation, omitted variables and unobservables - than to build more complex models which incorporate temporal dependence, feedback or transition costs.

Rigid adherence to specific patterns of shopping activity is unlikely to depend on earlier decisions. Instead, we note that the socio-economic circumstances of many consumers are shared. Consumers take on the norms of their peer group and locality, and they indulge in similar tastes and fashions, as a consequence similar behaviour patterns tend to be revealed.

4 Discussion

Models for the analysis of repeated choice have been developed and illustrated. This has been done for situations where there are two alternatives and many alternatives. Application of the beta-logistic and Dirichlet-logistic models enables us to conclude that:

(a) In the study of shopping behaviour there are important influences to consider: spatial and socio-economic factors measures of mobility, consumer attitudes, and variations in taste and fashion. These influences are incorporated directly into models (as variables) or ascribed to random variation (as unobserved heterogeneity and omitted variables).

(b) The beta-logistic and Dirichlet-logistic models fit the data well. This is true both for isolated components of activity (such as repeated mode choice) and for collective aspects of activity (such as repeated occupancy of activity bundles). The models also fit well when choice sequences are fixed (for example principal trips) and when the number of occasions varies (as when all trips are considered).

(c) Decisions made regularly over the short-term are not affected by feedback and intertemporal dependence. Therefore, models that are heterogeneous and zero-order are sufficiently well specified for our purposes. Recourse to higher-order stochastic models will not markedly improve predictions and will not give a better account of the data.

Arising from these conclusions are two major questions that need to be discussed: (1) to what extent do the findings presented in the foregoing sections generalise? and (2) what alternative approaches are available, or possible, which offer new insights? The remainder of this chapter addresses these two questions and ties together empirical results with the wider literature.

4.1 Evaluation

Generalisation is a subject that can be approached at several levels; two levels, the empirical and the theoretical, are discussed here.

4.1.1 Empirical Generalisation

To be valid (analytically and practically) models should be informative when applied under a variety of conditions. There are at least two aspects to this issue: first the transferability of models and then the transferability of findings. The range of disciplines involved in the development of panel data models is evidence enough of how well these models transfer.

While it is helpful to know that models transfer across the boundaries of disciplines, it might be more worthwhile to examine the consistency of findings. Findings that are true of consumer and labour behaviour, in the USA and in Britain, for public and personal transport, will help us to identify regularities and generalisations.

Many findings have been accumulated for the descriptive models that lie at the heart of the beta-logistic and Dirichlet-logistic models. These results generalise so that 'The Dirichlet model directly or indirectly describes the buying patterns that have been found for many different products, food and non-food, over many years in the UK and USA' (Goodhardt et al. 1984). Consistent results from a variety of contexts have enabled these authors to isolate many regularities, such as 'American and British repeat-buying habits are the same'.

Especially relevant is the finding that 'store-choice is like brand choice' (Wrigley and Dunn 1984b, 1984c, Kau and Ehrenberg 1984). Market share governs the amount of switching between stores and the level of duplicate purchasing at other stores; both switching and duplication are heavy and so store loyalty is low. Market share, itself, is determined by the number of customers to a store (ie. penetration within a sales region) and this is like brand choice.

Regression-type models are less likely to provide generalisable findings. They tend to be case-specific and sensitive to local circumstances. Nevertheless some findings are consistent, for instance, 'repeated mode choice is like repeated occupancy of activity bundles' and this is true for all and principal trips. Departures are easier to assess when results are stated in this manner, we then see that loyalty to particular activity bundles is usually lower than loyalty to travel mode.

A further consistent (if not generalisable) empirical finding is that 'the apparent influence of previous choice on current choices is the outcome of omitted variables and unmeasurables, and is not due to intertemporal dependence'. However, the domain of this discovery is strictly limited to short-term and stable conditions.

A sharp contrast is drawn between short-term decisions and major events in a person's life-history. Choosing a brand of toothpaste or selecting a form of travel is a regular decision, it is neither risky nor premeditated; whereas the decision to migrate depends upon ambitions, employment opportunities, residential preferences, costs of severance and is most clearly a purposeful act.

The spatial transferability of findings is one area of research that still requires thorough investigation. There is every reason to suppose that many findings will not transfer, simply because transport and retailing are organised differently in different countries. One would not expect patterns of behaviour in a mobile society where public transport is improverished to be similar to patterns in a city which possesses efficient rapid transit systems.

Some comparisons of parameter estimates from cross-sectional discrete choice models have been undertaken (Talvitie and Kirshner 1978) and results show that estimates are not transferable either within or between urban areas. Apart from real differences between areas, findings are likely to be influenced by wide variations in survey design, definition of variables and model specification.

Cross-cultural comparisons are beginning to emerge for panel data analysis: the Cardiff data is being compared against consumer behaviour in Santa Barbara, and AGB data collected in Britain is to be assessed against MRCA data collected for test cities in the USA. Problems that arise from variable sample designs remain, but results are likely to reinforce two points: salient descriptive features are transferable, whereas estimated parameters tend to be case-specific. Indeed, parameter estimates from models based on panel data may be less transferable than logit models if the impact of omitted variables and unmeasurable tastes varies across space and time. However, at least panel data enable these influences to be investigated explicitly.

Empirical work needs to identify and generalise the salient descriptive features of consumer behaviour (such as repeated patronage and duplication of patronage), then isolate those variables which are consistently good predictors of behaviour. Regression-type models are needed most when an understanding of behaviour is desired. Finally, if the project requires detailed appraisal of particular proposals, then contextual variables should be introduced (including distances and local features, alternative-specific variables, and attitudinal measures).

4.1.2 Theoretical Generalisation

The beta-logistic model is extremely flexible. Extension to the multi-alternative situation has been developed already. Now generalisation at a further three levels is discussed. Firstly, generalisation is possible within the theory of stochastic processes. The relationship between discrete and continuous time models points to another area of generalisation. Finally, attention to model robustness provides a common core in much of the recent work concerned with panel data and event histories.

(1) The general theory of stochastic processes

The emphasis of earlier sections has been upon zero-order models and a strict independence assumption has been imposed. As we saw when the beta-logistic model was compared against the first-order Markov process, sometimes the independence assumption may be relaxed. Under the first-order Markov process the system is driven by one-step transition probabilities. Further movement towards the specification of fully dynamic processes is possible through the development of queueing, renewal and recurrence models.

Heckman (1981a) has gone furthest to show how a variety of stochastic processes can be integrated into a unified approach. He proposes a generalised model for the analysis of panel data in which Bernoulli models, Markov models, renewal processes, etc are special cases which emerge when restrictions are imposed. In this generalised model choice at time t is a function of four major components:

(i) exogenous variables (past, current and future)

(ii) the entire past history of the process (several stochastic generating processes are envisaged)

(iii) accumulated experience in a single state (equivalent to a renewal process)

(iv) habit persistence (where prior propensities to select a state, rather than prior occupancy, determine the current probability that a state is occupied)

Heckman's general model can also handle time-varying exogenous variables, intertemporal dependence and serial correlation, omitted variables and heterogeneity.

A generalised beta-logistic formulation has been proposed by Davies (1984) for the analysis of residential mobility. In a very clear account Davies draws firm theoretical links between cross-sectional logit models and the beta-logistic model. He then shows how feedback effects and time-varying variables might be incorporated. From life-history records it is clear that duration-of-stay, nonstationarity and uncontrolled heterogeneity are important, whereas cumulative inertia is of less importance than previously believed.

Generalised beta-logistic models, however, are cumbersome in that initial conditions have to be specified to start the process and data is required for time-varying parameters. The final model is less parsimonious and computationally more expensive, this would be even truer if the existing binary examples were extended to the multinomial (Dirichlet) case.

(2) Discrete states in discrete and continuous time

Standard stochastic process theory distinguishes between discrete/continuous states and discrete/continuous time. Most interest focusses on the analysis of discrete states in discrete time and continuous time.

(a) Discrete events

All the examples quoted earlier dealt with discrete states in discrete time. Thus, consumers had to decide between two or more 'states' (travel by car, bus , ...) on successive occasions, where each occasion corresponds to an 'event'. In studies based on a sequence of events the spacing of time periods is of some importance. Weekly time intervals enable us to assume that the decision in one period is independent of decisions made before.

Shorter time intervals, however, may reveal patterns of behaviour which are not independent. In particular, an inventory effect is often observed immediately after an event has occurred.

The role of time periods in stochastic models is generalised by the Erlang operator. When time periods are measured in weeks inter-event purchase probabilities are exponentially distributed and the Erlang operator is of order 1. Inventory effects are captured when the Erlang operator is of order 2 or 3. Such a generalisation of purchase timing effects underlies the integrated model proposed by Jeuland et al. (1980).

(b) Durations

Duration of time until the next event is the topic of principal interest in models based upon discrete states in continuous time. Typically a record of events is available; these events are associated with entry and exit from states and the purpose of modelling is to predict the 'hazard' of staying or leaving one of these states. Such models have been applied in labour studies, mathematical demography and epidemiology. Recovery rates from malarial infection, labour force duration, probability of leaving unemployment - these are just a few examples (Heckman and Singer 1982, Lancaster and Nickle 1980, Hannan and Tuma 1983).

Retail and transport applications are less common, although one of the classic illustrations of queueing theory refers to consumers in a supermarket. The illustration considers the growth of a queue at a supermarket checkout; growth depends on the random arrival of customers and the time taken to serve them (waiting time). Other examples of continuous time processes can be envisaged; for example, purchase of a new brand or patronage of a new superstore may depend on the random diffusion of information through the target population. Heavy advertising may raise awareness among susceptible consumers, giving rise to many 'adopters' and deep market penetration. Diffusion studies of spatial marketing are described by Brown (1981) and much further work could be undertaken.

(3) Model robustness

Links are to be drawn with conventional time-series methodologies. Examination of serial correlation and residuals are the two primary concerns of time-series analysis. Each concern has similarities with the problems of model specification for panel data: serial correlation is related to the issues of intertemporal dependence and feedback; irrespective of whether cross-sectional or longitudinal models are being fitted, residuals and predicted probabilities ought to be inspected; and common to all modelling is the need to perform diagnostic tests, to assess parameter stability and to assess the sensitivity of responses. Work in econometrics is making important steps towards the provision of methods for the evaluation of serial correlation and residuals, for both discrete and duration data (Chesher and Irish 1984).

Geographers looking at model specification and model robustness in the time domain have largely worked with variants of regression analysis. Typical has been the research into leads and lags, parameter instability and time-varying parameters, spatial depedence and regional responses to national economic fluctuations (Bennett 1979, Cliff and Ord 1980, Dunn 1981, Hepple 1981). If 'residual-like' terms can be defined for quantal responses there is the possibility that links will be forged between conventional time-series methods and new panel data methods.

Intuitively we can imagine several applications: among a local consumer market one could examine the proximity in time and space of successive choices to patronise a store, or one could investigate how knowledge of a new store diffuses through a community. To the extent that spatial dependencies correlate with variables and with unobserved heterogeneity, some space-time influences are already incorporated within panel data models. Formal equivalence between these approaches has yet to be established.

These comments are speculative and the practical problem of forging links should not be under-rated:

(i) First, data requirements present difficulties. Most panels do not contain detailed location data and even the Cardiff panel does not sample individuals living in contiguous residential areas.

(ii) Second, the scale and time-span of spatial analysis has tended to be regional and long-term (eg. meso-scale economic responses and inter-regional movements) whereas the techniques presented here are designed for short-term analysis of micro-behaviour.

(iii) Third, emphasis has shifted away from forecasting towards the exploration of data and the isolation of the most salient features. Emphasis is now more narrowly focussed on the correct interpretation of empirical evidence.

4.2 Alternatives

Analysis in this chapter has been conducted within the confines of one modelling scheme: the parametric. In all cases the mixing distribution has been regarded as some form of beta distribution. Strong reasons to favour the beta distribution have been advanced, including the tractability, flexibility and consistency of models based on this distribution, the reliability of empirical findings and the parsimony to be achieved.

It should be noted that continuous-choice processes and the analysis of durations may be described more appropriately by other distributions. Heterogeneity might be represented by a gamma distribution, but regression-type models which assume a gamma distribution do not have the same appeal as beta-logistic models and empirical support is lacking. Further distributional assumptions can be incorporated; for example, Pickles (1983) captures duration dependence in a renewal model of residential movement by invoking a Gompertz distribution. But in short-term analyses such additional assumptions may give rise to a model that is over-specified.

Emphasis, quite clearly, has been on parametric methods. Yet little is generally known a priori about the distribution of heterogeneity 'There is virtually no theory' write Heckman and Singer (1982, 575) 'that guides the choice of mixing distribution'. These authors note that heterogeneity (from unobservables) is usually described by a distribution chosen quite arbitrarily and go on to show how parameter estimates (for observables) are sensitive to this choice. Alternative approaches include the application of empirical Bayes estimation (Rolph 1968) or adoption of methods that are non-parametric.

Scattered attempts have been made to apply non-parametric methods. The shape of the mixing distribution is not assumed a priori, instead the amount of unaccounted heterogeneity is assessed empirically and then expressed as a finite number of mass points. Maximum likelihood methods are used to estimate these models.

Through successive re-estimation of the model further mass points are identified. This process is continued until the addition of a further point does not lead to a noticeable change in parameter values. Those parameter estimates which correspond to the final number of mass points are adopted as the true (ie. asymptotically consistent) ones.

Mass point methods build on the work of Kieter and Wolfowitz (1956) and Laird (1978), and have been applied to the study of residential mobility by Davies and Crouchley (1984) and Davies and Pickles (1985).

To some extent the criticism of parametric methods is overstated: consistent parameter estimates, which have meaningful interpretations, are available when a beta distribution is assumed. Many researchers have converged on the beta form because of a complex interplay between data and theory, so the choice is not arbitrary. Moreover, mass point estimation is not devoid of difficulties:

(a) To characterise all unobserved heterogeneity in a substantial empirical problem many mass points are required. Search for a global optimum involves protracted re-estimation of the full model, and computation becomes inefficient.

(b) Mass-points are totally case-specific, so no common basis exists for the comparison of higher moments. Indeed, while parameter estimates associated with observables are reliable, the characteristics of the mixing distribution may be described inaccurately (Heckman and Singer 1982). As a consequence the interpretation of omitted variables is difficult.

CONCLUSION

With a sudden intensity, as if she saw it clear for a second, she drew a line there, in the centre. It was done; it was finished. Yes, she thought, laying down her brush in extreme fatigue, I have had my vision.

Virginia Woolf (1927)
'To the Lighthouse'

1 . Summaries

At the end of each section findings have been summarised, and possible extensions have been discussed. Some of the more important points are reiterated in this concluding statement.

The behaviour and activity of consumers has been studied. Attention was given to the decisions and movements of shoppers, especially those aspects which are repeatedly associated with the purchase of grocery goods. The approach has been empirical and has sought insights into how consumers behave. All substantive findings were based upon the Cardiff consumer panel.

A number of ground-rules have been followed in doing the empirical work and these might be regarded as a useful set of strategies to follow in other projects:

- check the data first
- see what information can be obtained from simple descriptions
- use models when data need to be probed more effectively
- select models that identify the salient messages
- don't construct elaborate models when simple ones are good enough
- assess the models
- interpret the findings

Then, communicate the findings. These ground-rules have left their mark on the results that are summarised below.

The reliability of subsequent analyses depends on the quality of the input; this issue was addressed in chapter 1. Panel data were shown to be an admirable source for the study of shopping activity and, in particular, the Cardiff consumer panel was found to be reliable. The extent of bias and inaccuracy was less severe than expected. Attrition was under control and the main features of consumer behaviour proved to be stable and repetitive. Diary records provide a rich source of disaggregate data that can be collected without the imperfections of memory recall.

The basic features of grocery shopping were described in chapter 2. Special attention was given to temporal rhythms, movement, multi-stage trips and multi-purpose trips. One important finding is that patterns of activity have changed little since the late 1960s: morning trips made on foot have remained dominant and most shoppers continue to undertake about 4 to 5 grocery trips each week.

The latter part of chapter 2 looks at the influence of the personal circumstances of shoppers. This information is used to specify models in part II, but much of it is useful in its own right. For instance, findings show that:

- Working women economise on non-work activity and defer some travel to the weekends; yet, generally, roles within the family have changed remarkably little over recent decades.

- Mode choice and patterns of shopping movement are determined by an individual's access to private transport. Access itself depends upon household wealth, personal circumstances and the division of responsibility within a family.

- Most shoppers move within very restricted activity spaces. There are strong distance decay effects away from the home, workplaces and familiar routeways. Organisational constraints, such as bus timetables and the radial pattern of bus routes, further narrow the scope for freedom of movement.

The discussion shifted to formal models. This move was justified in order to provide a more disciplined and effective description of the data.

Classification of complex behaviour into a small number of activity bundles was achieved in chapter 3. The structure of these bundles depended on whether principal or all trips were considered:

- Principal trips are differentiated by the form of travel to reach shops and by the quantities bought. The sharpest division is between bulk-buying on car-borne trips, and lighter shopping when travel is by foot.

- The collection of all trips is more varied. Much depends on the relative location of shops and homes, and on other activities, as well as access to vehicles. The dominant group describes trips that cover short distances on foot and where buying is light.

Studies of stability show that similar classifications are generated week-by-week. Also, alternative methods convey similar messages.

Chapter 4 presents several illustrations of cross-sectional methods and simple regression-type models that are adapted for the study of consumer activity:

- Poisson models describe the incidence and timing of shopping trips and reveal the important influence of work and income. These influences affect the amount of discretionary time that is available.

- The choice of when to shop, studied using logit regression, depends on the age of a shopper and family structure, especially the presence of children.

The best of these models are carefully assessed in order to detect extraordinary observations and to gauge their impact upon model sensitivity. Other tests and checks are discussed too. These studies confirm that our original models are reasonably robust and illustrate the important role of diagnostic procedures. However, there is a sharp difference in the performance of single-component models (for example the decision to shop during the early evening) and models of daily incidence; only the former perform well. Moreover, if spurious statistical effects are to be separated from true effects (such as variation among the sample members and tempoaral dependence) then longitudinal models are required.

An integrated approach was illustrated in chapter 5. Full advantage was taken of the longitudinal nature of the consumer panel. In particular, models for the analysis of repeated choice have been developed and illustrated. This has been done for situations where there are two alternatives and many alternatives. Application of the beta-logistic and Dirichlet-logistic models enables us to conclude that:

- In the study of shopping behaviour there are important influences, these include spatial and socio-economic factors, measures of mobility, consumer attitudes, and variations in taste and fashion.

- The beta-logistic and Dirichlet-logistic models fit the data well. This is true for isolated components of activity (such as repeated choice of travel mode) and for collective aspects of activity (such as repeated occupancy of activity bundles). The models also fit well when choice sequences are fixed (for example principal trips) and when the number of occasions varies (as when all trips are considered).

- Decisions made regularly over the short-term are not affected by feedback and intertemporal dependence. Therefore, models that are heterogeneous and zero-order are sufficiently well specified for our purposes. Recourse to higher-order stochastic models will not markedly improve estimates and will not give a better account of the data.

2 Postscript

Many themes developed in this thesis penetrate the whole of modern quantitative geography. Shared by most recent studies, for instance, is the emphasis given to the 'movie' of activity rather than the 'snapshots' of form. In all this research it is recognised that time and space are strongly interconnected, and that a full understanding of urban processes will only arise after much detailed study. Such an examination invokves careful empirical observation at micro and meso scales, and thoughtful integration at the macro scale.

Aggregate studies of time series and dynamic systems analysis initially brought the temporal dimension within the ambit of geography (Bennett 1979, Batty 1976, Embleton and Thornes 1979, Wilson 1981). This approach transcended the whole discipline, from urban traffic planning to environmental control. Recently the tendency has been to focus upon components of the system and to discover the mechanisms that lead to change. Simulations of retail change, of the decentralisation of economic activities and of people's access to community facilities are typical of this research (Fotheringham 1985, Clarke et al. 1985).

Through these meso scale analyses there appears to be a coming together of systems modelling and empirical data analysis. I believe that Yuill (1968) and Lenntorp (1978) in their empirical and simulation studies of personal movement and space-time activity were moving toward such an integration, but they lacked the data-base to pursue their work to its logical conclusion. Panels, which contain a uniquely rich source of temporal and spatial data, ought to provide a basis for integration.

The affinity that exists between these different approaches means that many issues are open to common debate, notably: scale and resolution, induction and deduction, rates of change and stasis. It is in respect of these more specific debates that the work presented in this thesis differs from that which has gone before. Therefore, while the temporal component is upheld, the aim is simply to find out how best to describe what people do in time and space. Models, recall, are a disciplined way to tell a story.

Lily Brisco, in 'To the Lighthouse', drew a line on her canvas and decided that her painting was done; it was finished. Ours, by contrast, is a story that refuses to finish. In the short-term work is being done to see how well models and findings transfer between different cultures, to assess the parametric assumptions of longitudinal models, and to discover alternative ways of testing the validity of models.

Over the longer-term it is to be hoped that full advantage will be taken of advances in computer technology: to collect data, to analyse and probe data, and to disseminate results. Once it is known how to describe the behaviour and activity of consumers we can probe deeper into their perceptions and find out how the routines of many individual agents combine to shape the future character of our cities.

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One's training is certain to influence the style of work that one undertakes, and the seeds of several ideas presented in the preceding pages were first sown when I was an undergraduate student at Bristol. My interest in disaggregate models and diagnostic tests is due to the influence of Neil Wrigley and Les Hepple. The emphasis that I give to space-time studies, and urban modelling in general, arises from Peter Haggett's guidance. Such a broad training means that it is hard for me to think in terms of fixed and narrow compartments; this attitude of mind has been a tremendous help.

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