DURATION DEPENDENCE IN LONGITUDINAL CONSUMER PANEL DATA

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CONSUMER PANEL DATA:

A CONTINUOUS–TIME, STOCHASTIC MODELLING APPROACH

By

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ABSTRACT

Due to growing competition for market share, the retail environment is becoming increasingly specialized. Consequently, current retailing practices are concerned with targeting both spatially and aspatially defined population segments which, in turn, has led to the need to acquire detailed information on individual purchasing patterns. The collection of longitudinal data associated with the development of 'scanner panels' will result in a consumer behaviour data explosion, generating extensive, spatially disaggregate and detailed purchasing histories recorded at the individual level. A crucial element in the use of 'scanner panels' for retailing practices resides in the development of appropriate methodologies for analyzing this data and methods which exploit fully the information contained in these detailed records.

This thesis considers the application of an event–history modelling approach to consumer shopping behaviour using longitudinal data from the Cardiff Consumer Panel, 1982. The focus of this research is duration dependencies involved in store switching behaviour. It is reasoned that the probability of choosing a particular type of retail outlet depends on both the type of store visited in the preceding trip and the time elapsed since that trip. Duration dependence between store switches can then be expressed in the distributional form of the hazard rate.

Results indicate that an event–history approach provides a valuable methodology for examining consumer shopping behaviour. Duration dependence is found to be an important influence on store switching behaviour and the distributional form of duration dependence is seen to vary with different types of stores. Furthermore, measured sources of heterogeneity contained in such models indicate how different individual characteristics may be important in explaining the store choice behavioural process.

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Inconvenience stores

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CHAPTER ONE

INTRODUCTION

1.0 Trends in the Retail Environment

The retail environment is determined by and determines consumer purchasing behaviour. The spatial distribution of consumption patterns for goods and services is directly related to both the product type and the size of the distribution outlet. Retailers, therefore, select the distribution of goods and services by their degree of product specialization and their scale of operation. Stores create a geography of demand by attracting consumers, channeling travel patterns and consequently affecting the location of other stores (Gautschi, 1981; Jones & Simmons, 1987). Demand and supply operate jointly in the retail environment, linked by behaviour patterns of consumers, who decide how far they are willing to travel to a store and what variety of goods and services they expect. Throughout the postwar years profound organizational and spatial restructuring of consumer oriented industries occurred which has contributed significantly to the transformation of the urban landscape.

Since the late 1950's there has been an overall expansion of consumer oriented industries and retailing, in particular, has become increasingly important to urban economies. Expansion in retailing has been characterized by a decline in the number of store outlets against a background of increases in the real volume of retail sales (Guy, 1985; Jones & Simmons, 1987; McGoldrick, 1987; Wrigley, 1988). This has resulted in an enormous concentration of activity within a limited number of retailers so that a small number of actors now play a disproportionate role in forming the retail structure.

Capital concentration has been a primary driving force behind organizational restructuring of consumer oriented industries and this, in turn, has resulted in the emergence and expansion of large retail corporate chains (those operating 100 or more outlets). The huge positive net cash flows generated by these corporations means that capital requirements for investment in new, larger stores (often on new sites) is available. One result of this restructuring has therefore been an increase in the average size of stores and these larger stores have captured trade at the expense of single outlet retailers and smaller corporate chains. The market is currently dominated by these larger stores, and this is particularly clear in the case of grocery retailing. For example, in 1982 the five largest corporate chains in Britain accounted for 43 percent of total retail food sales (Wrigley, 1988), and in Canada, over 50 percent of the total retail food sales of 1985 were attributed to the top four chains (Jones & Simmons, 1987).

Capital concentration and the resulting emergence and expansion of retail corporations has lead to a fundamental shift in the balance of power away from the manufacturers/supplies of consumer goods to the distributors of these goods (Guy, 1985; Lamb & Goodhardt, 1988; Lewis, 1985; McGoldrick, 1984; Reader, 1988; Wrigley & Dunn, 1988; Wrigley, 1988). Large retail corporations have increased their market power through vertical integration, and in retailing, this has meant that corporations expand operations into wholesaling and production activities, guaranteeing a supply of goods of specific quality (Guy, 1985; Jones & Simmons, 1987; McGoldrick, 1984; Wrigley, 1988). Retailers now assume the once dominating role of manufacturers in terms of merchandising, advertising and market research and, consequently, retail chains now have important purchasing power because of their leverage in negotiating with manufacturers.

Increased retailer purchasing power is apparent from development of 'own brand' labels, practiced in the clothing and footwear industries for many years but, a more recent phenomenon in the grocery sector and one that appears to be gaining in popularity (Strauss, 1990). A more recent innovation adopted by major retail chains has been the development of generic or 'no–name' product lines, frequently introduced as a second or even third retailer label range. The development of generic products has been most prevalent among grocery retailers (McGoldrick, 1984), a current example of which is the introduction of generic "green products", developed to satisfy current trends towards environmental consciousness. Such specialized product lines are specific to particular retail chains and have resulted in increased analysis of individual stores and individual products, to assess their contribution in terms of profit and customer attraction.

Several large retail chains have also integrated horizontally, increasing their market power and enabling them to diversify into related (retail) activities using common expertise or facilities. As a consequence of this integration, the development and evaluation strategies of these organizations has changed since market actions taken at different sites have become interdependent, so that retail chains have shifted focus to examine system–wide profit and loss rather that the profit of any one outlet (Jones & Simmons, 1987). Furthermore, several corporate chains have increased their efficiency and economy of operations by restructuring their distribution systems; replacing the older, direct manufacturer/supplier to store method with centralized, in–house distribution systems (Lewis, 1985; Wrigley, 1988). This in turn, has standardized distribution operations across large, spatially defined markets and has resulted in more sophisticated systems of stock control both within individual stores and within parent organizations.

Trends in the organizational and spatial restructuring of consumer oriented industries are not only a function of supply side changes (ie. those of retailers), but also reflect spatial changes in consumer behaviour and demand. Dramatic spatial change in consumer behaviour, post–WWII, has been due to suburbanization: the redistribution of households from a downtown core to the outer urban edges (Jones & Simmons, 1987; McGoldrick, 1984; Wrigley, 1988). Suburbanization has diminished the relative importance of downtown retail activity and has created concentrations of demand in suburban, outer suburban and urban fringe areas. Car ownership has increased and occurred in conjunction with suburbanization, permanently altering consumer behaviour (Gautschi, 1981; McGoldrick, 1984; Wrigley, 1988), by enabling households to travel further to shop and to carry more items from any one visit. Increased car ownership has moderated the constraint of distance on shopping behaviour, and this combined with demand created by suburbanization, has spatially transformed consumer oriented industries, with one result being retail development in suburban areas (the birth of the planned shopping mall) and redevelopment in downtown locations.

Most recently, downtown redevelopment has occurred in response to gentrification and counter–suburbanization, changing the social character of inner city locations due to the infiltration of professional/higher income groups. This has resulted in a rejuvenation of downtown retailing activities (Jones & Simmons, 1987) because of new demand for goods and services created by the influx of this segment of the population. Furthermore, the establishment and growth of ethnic neighbourhoods has spatially transformed urban retailing (Jones & Simmons, 1987). These once small neighbourhood shopping areas have evolved to the point where they now cater to members of the ethnic community throughout the metropolitan area and, in some cases, have become tourist attractions.

Overall, urban populations have become spatially segmented, creating dispersed markets with distinct patterns of consumer behaviour. Such spatial changes in consumer behaviour have not been uniform across social classes and age groups but rather have produced differential shifts in consumer demand. These shifts have been discussed in detail elsewhere (see Jones & Simmons, 1987 for the changes observed in Canada; Wrigley, 1988 for the changes in Britain) and will not be reviewed here. Suffice to say that these differential shifts have led to increasing spatial variation in consumer demand, and, for operations to succeed, this spatial variation of consumer demand must be accommodated for by retailers and retail corporations.

Marketing techniques have adapted to the spatial variation of consumer demand by establishing merchandising, locational and advertising strategies particular to socio–economic and spatially defined markets. Conventional mass–marketing schemes, with broadly–based consumer appeal, are giving way to 'target' marketing of subpopulations (Collins, 1989; Fotheringham, 1988; Jones & Simmons, 1987). 'Target' marketing (also known as niche marketing or segmentation), focuses on a particular market segment (such as suburban households, card–holders, etc...) and conducts merchandising, locational and advertising strategies specific to that segment.

Retailing is becoming increasingly specialized due to growing competition for market share. This is reflected in marketing practices targeted at both spatially and aspatially defined population segments. Market saturation may be considered as a spatially defined marketing technique and operates by developing a large number of low–cost sites, emphasizing convenience and availability, while reducing overhead costs (for example, the development of 24 hour retail convenience stores). Such stores cater to particular, spatially defined, segments of the population, offering a wide range of products (both grocery and non–grocery items), and servicing neighbourhoods or accommodating travellers (by locating on major routeways). An example of aspatial market specialization is seen in the development of "retail warehouses", which offer a limited product range and are price sensitive to particular socio–economic segments of the population. "Retail warehouses" are the most recent variant of planned suburban malls (Jones & Simmons, 1987), decreasing costs by such strategies as less glamorous store design, reduced customer service, minimal store fixtures and reliance on products that are over–runs, end–of–line or factory seconds. "Retail warehouses" are most prominent in non–grocery retailing (Lewis, 1985), such as furniture or factory outlet centres, and are geared towards lower income households. The dominance of large retail chains has been further strengthened by these specialized marketing strategies, since retail corporations have the investment capital needed to adopt these practices and corporations can spread the associated costs over a number of facilities.

Specialty retailing is an alternative marketing scheme which can be spatially dispersed or clustered, depending on whether or not specialization emphasizes specific merchandise, or focuses on a certain set of consumers (Jones & Simmons, 1987). Dispersed (or aspatial) specialty retailing includes retailers who offer a highly specialized product (such as, antiques, kites, model trains and gourmet foods), and who have no need to form spatial concentrations, since they rely on consumer motivations for their one–of–a–kind type merchandise. Clustered (or spatial) specialty retailing describes retailers who concentrate spatially in specific locales, in order to reach a particular segment of the population. Clustered specialty retailing provides a comparison shopping environment in which consumers are attracted by the variety offered by a group of stores selling similar goods. This type of marketing strategy focuses on the social function of shopping, and includes developments such as historical redevelopment properties and theme malls. The rapid growth in both product specialization and specialty retailing has added a new aspect of competition to the retail environment (Collins, 1989; Jones & Simmons, 1987). Independent merchants and some of the specialized chains are competing for market niches to provide unique shopping alternatives. In response, conventional malls have tried to develop more distinctive images, for example, by the kiosking of designer clothes in downtown retail department stores for targeting sales at young urban professionals.

As a result of current trends in the retail industry, therefore, it is apparent that an increasingly competitive retail environment is developing. This environment will demand national, regional and intra–urban scale responses to preserve and/or enhance a firm's marketing position (Wrigley, 1988; Reader, 1991). However in an era which will witness widespread low growth rates for the retail industry, competition in relatively few high–growth rate areas and an increasing number of retail giants, it may be argued that only the intra–urban scale will consistently provides opportunities for new retailing strategies. These strategies will involve spatially disaggregate target marketing practices to accommodate the spatially segmented and diversified behaviour of current consumers. Consequently, these retailing strategies will require detailed knowledge of consumer purchasing patterns at a disaggregate (or individual) level.

1.1 Technological Innovations in Retailing

Technological innovation has changed the retail environment by altering demand, supply and distribution of goods and services. By technology we here refer to technical advances in the methods of acquisition, distribution and production of goods and services. As mentioned earlier, the introduction and proliferation of car ownership has permanently modified spatial patterns of consumer behaviour. Increased freezer ownership has also dramatically altered grocery shopping patterns, sustaining the trend towards fewer, larger shopping trips (McGoldrick, 1984). Modernization of retail supply and production methods has occurred through the growth in store sizes, the innovation of electronic cash registers and the wide–scale adoption of self–service operations amongst others. These trends reflect the organizational restructuring in consumer oriented industries discussed previously and are also, in part, responses to increasing competition in the retail environment. Investment into larger stores means that retail corporations are more able to take advantage of economies of scale, which in turn, has been facilitated by the adoption and popularization of electronic cash registers and self–service strategies. Electronic cash registers and self–service operations have become standard retailing practices and have resulted in an overall reduction of the retail workforce which, in turn, has resulted in compositional changes of the remaining workforce. There has been a growth in the number of women's jobs (particularly part–time), a decline in the number of men's jobs and an increasing polarization between a small number of highly skilled managers and a much larger group of routinized and often part–time workers (Lewis, 1985; Wrigley, 1988).

Technological innovation in retail distribution has been facilitated by capital concentration of large retail corporations. Several of the major retail chains have invested in computer–based information technology, thereby increasing the efficiency and productivity of centralized distribution systems while reducing distribution costs (Guy, 1988; Jones & Simmons, 1987; Lewis, 1985; Wrigley, 1988). Initial introduction of these computer systems was confined to particular areas of activity and did not link stock control/distribution, administration and sales together into integrated management information systems. However, integrated management systems are on the increase (Lewis, 1985) and are built upon in–store electronic point–of–sale (EPOS) systems.

EPOS systems consist of a laser scanning device at checkout counters which reads the universal product codes (UPC or 'bar codes') printed on individual products, which are, in turn, cross–referenced against prices held on a central in–store computer. As the product is scanned, the point–of–sale (POS) system identifies the product, produces an itemized receipt for the customer and automatically adjusts sales statistics and store inventory levels. EPOS systems significantly improve stock management, including faster and more accurate stock reordering and reduced stock holding, and have the potential to automatically order stock for delivery and to make goods ready for dispatch from automated warehouses. Furthermore, these electronic point–of–sale (EPOS) systems may be linked with electronic fund–transfer (EFT) systems, creating EFTPOS systems, which automatically debit the customers bank account when a purchase is made, and if linked with an electronic accounting system, retailer stock invoices could be matched and automatically paid.

The use of EFT systems is not new in consumer oriented industries. The banking industry, for example, has used electronic fund–transfer systems in automatic teller machines (ATM's) since the early 1980's (Allaby, 1986a, Weil, 1982). Possible extensions of EPOS/EFTPOS systems in grocery retailing include the production of individually–tailored, automated product coupons at the point of sale (Ktokis, 1987); the use of videocarts[1] in grocery stores; and home shopping and viewdata systems (Bennison, 1985; Guy, 1985). Furthermore, EPOS/EFTPOS systems may be used in combination with split–cable technology, enabling monitoring of household television viewing behaviour in association with consumer purchasing behaviour (Lodish & Reibstein, 1986). Information provided by EPOS/EFTPOS systems has the potential to provide retailers with detailed data on comparative sales of different products, brands and stores and to track changes in sales over time. This type of information could also be used to monitor the effectiveness of price changes, promotional campaigns and the buying patterns of different types of consumers. By utilizing such data retailers could then devise

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[1]Videocarts are shopping baskets mounted with video terminals which advertise products on sale as a consumer travels through store aisles.

merchandising, advertising and locational strategies particular to both spatially and aspatially differentiated target markets.

One form of consumer data that information technology is threatening to revolutionize is that of the consumer 'panel data' set. 'Panel data' is data which records the individual purchase decisions of the same group of consumers over time. Manually collected diary panels have conventionally been used to obtain longitudinal data for consumer behaviour analysis but these diaries are completed at periodic intervals by the consumer and rely on an individual's recall after the behaviour has already taken place. Typically, the information from manual diary panels is collected at temporally aggregate levels (weeks or months), over a limited geographic area, and has largely been used for macro–scale studies (such as, tracking brand shares and new product launchings) (Ehrenberg & Goodhardt, 1970; Parafitt & Collins, 1968). The collection of panel data is changing through the introduction of 'scanner panels'. 'Scanner panels' have created a consumer behaviour data explosion as they result in extensive, spatially disaggregate and detailed purchasing histories recorded at the individual level (Allaby, 1986a; 1986b; Gollins, 1989; Guy, 1988; Holmes, 1986; Ktokis, 1987; Lodish & Reibstein, 1986; Reader, 1988; Reader & Uncles, 1988; Takei, 1987; Uncles & Ehrenberg, 1988; Wrigley, 1988). 'Scanner panels' are EPOS/EFTPOS systems linked with 'smart cards' (or 'valued customer cards') which identify the consumer as a panel member. Upon panel recruitment a consumer is issued with a plastic 'smart card' which accesses information on their geodemographic features. At the point–of–sale, a customer hands the card to the cashier who then uses it to identify the panellist to the EPOS/EFTPOS system, which then generates a data record of the purchases made by the panellist.

The integration of smart cards and information technology (ie. scanner panels) is a recent phenomenon which is rapidly gaining momentum, especially in grocery retailing. Currently, the most advanced scanner panel system is BehaviourScan, of Information Resources Inc., U.S.A., which is established in 28 markets for a sample of 60,000 households (Gollins, 1989). Another example is Ukrop's Valued Customer program which is associated with Citicorp POS Information Services, U.S.A.. A consumer is rewarded for participating in Ukrop's scanner panel program by receiving customized coupons, electronically deposited into the panellist's data record, which are automatically debited from the price when the product is bought (Ktokis, 1987).

Scanner panels offer many advantages over conventional, manual diary panels. Firstly, the unprecedented detail offered by scanner panel data and the enormous amount of information contained in the observation records will supply retailers with accurate, up–to–date information on the behaviour patterns of consumers. For example, a purchasing record for one product category may contain information on a panellist's identity, the week/day and time of purchase, the bar code of the product, the number of units purchased, the price, coupon usage, store identification, store display, etc.... In addition, the scanner panel data set can be cross–referenced with a purchasing record file and thus may include information on the panellist's socio–economic status, store environment, television commercial exposure, bar code dictionaries and attribute data of the product itself. Secondly, the effort on the part of the panellist is minimal and this leads to reduced panel attrition rates whilst the incentive offerings (such a Ukrop's electronic coupons) lead to higher initial sign–up rates. Thirdly, the costs of introducing and maintaining the scanner panel is relatively small compared to the amount of information being obtained and savings are also associated with reducing administrative costs involved in supervising panellists.

Scanner panels provide a wealth of consumer behaviour data at the individual level and, in particular, repeat observation on each individual. The unprecedented amount of information contained in these purchasing records will only be useful to consumer–oriented industries if meaningful information on consumer behaviour can be extracted from scanner panel records. Consequently, a crucial element in the use of scanner panels is the development of appropriate methodologies, for analyzing this data, and methods which exploit fully the information contained in these detailed records.

1.2 Consumer Behaviour Studies

A number of disciplines examine consumer purchasing behaviour, notably psychology, sociology, anthropology, economics and geography. As a consequence of this multidisciplinary approach, studies have concentrated on different aspects of consumer behaviour considered at different levels of aggregation. In other words, studies of consumer behaviour have been conducted at the level of individual purchasing decisions through examination of individual/household buying behaviour, and at an aggregate level, focusing on changes in demand and supply of the consumer population as a whole. Studies relevant to consumer behaviour conducted in psychology, sociology and anthropology generally adopt a behavioural approach and are concerned with understanding individual cognitive processes which manifest in purchasing decisions. In a 'cognitive–behavioural' framework, individual purchase decisions typically depend on at least three components: deciding to purchase, the search for a set of alternatives and the actual decision between alternatives (Recker & Kostyniuk, 1978; Thrift, 1981). These 'cognitive–behavioural' studies facilitate understanding of the decision–making processes of individuals, but are limited in a mathematical modelling context because the *linkages* between perceptions, preferences and decisions are not empirically observable (Johnston & Wrigley, 1981). These studies seldom provide solutions to specific purchase decision problems (Fischer & Nijkamp, 1985; Hansen, 1972) but are useful for conceptualizing the variables involved in individual decision–making processes.

In economics, forecasts of consumer behaviour are often based on aggregate choice data, which assumes that the individuals composing aggregates are basically similar in terms of the decision–making processes which underlie purchase choices (Meyer et al., 1980). However, this homogeneity assumption is not based on empirical observation, nor is it rooted in empirical theory of individual consumer behaviour and, while useful summary statistics may be provided by such aggregate studies, they are unlikely to provide reliable forecasts of consumer behaviour changes (Bacon, 1984; Davies & Pickles, 1987; Hansen, 1972; Koppelman, 1974; Meyer et al., 1980; Reader, 1988; Wrigley & Dunn, 1984a).

The dominant contributions of geography to understanding consumer purchasing behaviour are from theoretical and empirical research involving Central Place theory and spatial interaction studies. Within a Central Place framework, an individual is assumed to purchase at the nearest source of supply and this assumption in turn, is linked to the behavioural assumption that on any given shopping trip a consumer will buy just one good (or equivalently, will visit only one store). Spatial interaction approaches are based on the notion that purchase decisions are the outcome of spatial choice processes, in which individuals select one alternative from a set of alternatives which have fixed spatial locations. The rigid geometry often imposed by these studies only allows the identification of consumer patterns on a broad, aggregate scale and therefore they may not fully recognize the dynamics of consumer behaviour (Bacon, 1984; Curry, 1967; Wilson, 1988). These assumptions imply that only limited interdependence exists between spatial choice processes, however multi–purpose/multi–stop trips are commonly observed in empirical studies of consumer behaviour (Allison, 1984; Bacon, 1984; Davies & Pickles, 1987; Fotheringham, 1989; 1988; 1986; Preston & Takahashi, 1988; Wrigley

& Dunn, 1984b; 1984c) and, while these geographical approaches provide the basis for examination of multi–purpose and multi–stop trips, they do not inherently address dynamic trip–making behaviour. Furthermore, empirical evidence, largely from the retailing literature, suggests that the tradeoffs existing between alternatives are not solely a function of distance but also depend on store characteristics (for example, the size of the store or the diversity of products carried) as well as consumer characteristics (for example, individual preference and motivation) (Davies & Pickles, 1987; Gautschi, 1981; Kau & Ehrenberg, 1988; Lamb & Goodhardt, 1988; O'Kelly, 1981; Wrigley & Dunn, 1985d).

Criticism such as this has resulted in a general dissatisfaction with aggregate approaches to consumer behaviour and a resulting movement towards disaggregate studies. Disaggregate studies are concerned with examining consumer behaviour at the individual (or household) scale and disaggregate models are based on postulates about the behavioural process of individuals. Disaggregate (or individual–based) models can be aggregated according to well–defined rules (Massy et al., 1970) whereas aggregate models make assumptions concerning the behaviour of population aggregates directly.

One limitation to date of disaggregate studies is lack of data at the individual scale but the advent and implementation of scanner panels seems set to produce overwhelming amounts of detailed purchasing histories at the individual level. Disaggregate methods will likely result in a better, more complete understanding of consumer purchasing because they incorporate features of individual behaviour which observation shows to be important.

1.3 Conclusions

Structural shifts in consumer oriented industries have resulted in the development of increasingly aggressive marketing strategies which have consequently produced a new emphasis on obtaining detailed, spatially disaggregate consumer behaviour information. The role of consumers is more crucial today than ever before since their needs have become so diversified and individualized, reflected in the greater number of differentiated and specialized markets. Technological innovation has dramatically altered retailing industries, increasing the efficiency while reducing the costs associated with production and distribution. The impact of technological change will radically change the acquisition of consumer behaviour data, the range of information collected, and the methods used to analyze such data.

Scanner panels are revolutionizing the collection of longitudinal data. They provide details of spatially disaggregate consumer purchasing behaviour. The introduction of EPOS/EFTPOS and scanner panel systems will likely result in greater understanding of consumer behaviour because of the detailed information these systems provide. Retailers can feedback this information into merchandising and advertising strategies and hence into marketing and planning decisions which, in turn, may increase their profitability or market share by satisfying the consumer demand which observation shows to be important. This revolution in the collection of consumer behaviour data will stimulate the development of modelling approaches suitable for handling such large volumes of data, and approaches that fully exploit the information contained in individual records.

The structural shift away from manufacturers, towards retailers, along with the associated trends in marketing, has led to a growing perception of the need to shift the focus of models of consumer purchasing behaviour from their traditional (aspatial) manufacturing / brand–choice orientation, (concerned with examining the buying patterns of brands or products), to a (spatial) retailer/store–choice orientation, (where interest lies in studying store choice behaviour). In consumer research studies, spatial marketing is an underdeveloped topic relative to that of brand choice. This is attributable, in part, to the historical dominance of manufacturers in the consumer goods industry but is also partly due to the greater complexity of the store choice issue, where shopping choices are made from spatially defined alternatives. The inherent spatial aspect in store choice decisions is often accommodated in marketing research studies by adopting aspatial definitions for store choice, using criteria such as store type or ownership. This, however, is insufficient because the choice of shopping destination is influenced by and influences the spatial activity patterns and behavioural experiences of individuals, a reality which is not inherently addressed in brand or product studies. Consequently, there is need for the development of empirically–based, generalized, spatially disaggregate models of consumer behaviour which address the empirically observed, dynamic nature of consumer behaviour.

1.4 Thesis Problem and Research Outline

The aim of this thesis is to provide insight into the nature and influence of time dependence in individual spatial choice processes. In particular, the focus of the thesis is the role of duration dependence in the store switching patterns for grocery product purchasing. In this context, duration dependence is defined as the amount of time a consumer remains loyal to one store type before switching to another store type. Therefore, the premise of this research is that duration dependence influences consumer shopping behaviour and the form of this influence is expressed in the distributional form of duration dependence.

Reviews of different modelling approaches to consumer behaviour exist elsewhere (for example, Allison, 1984; Blossfeld et al., 1989; Fischer & Nijkamp, 1987; Kalbfleisch & Prentice, 1980; Mahatoo, 1985; Massy et al., 1970; Timmermans & Borgers, 1989; Tuma & Hannan, 1984), but none of these works fully explore the multidisciplinary nature of the consumer purchasing behaviour literature. Largely due to this multidisciplinary nature, consumer behaviour research has examined the influence of time dependencies in consumer decision processes from a number of different perspectives. Within a 'cognitive–behavioural' framework the influence of time dependence is expressed in terms of learning and feedback processes that an individual experiences as being a part of a consumer–oriented society. Through learning and experience, individuals acquire knowledge about themselves, their needs, attitudes, motivations and about their purchasing environment (for example, product availability, prices and store locations). This knowledge is then utilized during decision–making and results in experience which becomes information that may be recalled in future decisions.

On the other hand, in an aggregate modelling framework, time dependence in consumer processes is either ignored, or is assumed to only implicitly influence purchase choices. Earlier aggregate–based studies, particularly in marketing research and geographical literature, concentrated on those aspects of consumer behaviour such as brand/store choice and purchase incidence/trip generation models and investigations were largely conducted in mutual isolation. Application of aggregate methods typically employs 'simple' distributional models and have tended to involve some degree of aggregation, particularly in the time dimension. More recent studies have begun to disaggregate these models by making the parameters of the distributions depend population heterogeneity (Broom & Wrigley, 1983; Jones & Zufryden, 1980; Wrigley & Dunn, 1984a) but behavioural variation due to time dependence has been relatively neglected. In the microeconomic literature, consumer purchasing model specification can accommodate individual buying choices, but most often these models are used to make predictions about aggregate behaviour. Traditionally, microeconomic studies ignore time dependencies in the decision–making process (Domencich & McFadden, 1975; Recker & Kostyniuk, 1978; Wrigley, 1975), but more recent studies have begun to address the dynamics of purchasing behaviour (Davies, 1984; Dunn & Wrigley, 1983; Tardiff, 1980).

However, there has always existed a body of literature in geography and marketing research which has explicitly considered time dependence in behavioural processes. Such work is based in stochastic behaviour theory and can be stated formerly through the use of various types of Markov models. Such models examine the influence of time dependence in terms of conditional probabilities, that is, the probability of purchase is considered dependent on previous purchases. The patterns of consumer shopping represent routine, repetitive behaviour in which the bounds of time and space are interlinked. Chapter 2 provides a comprehensive review of these various consumer purchasing behaviour modelling approaches which emphasize time dependencies as well as the spatiality involved in consumer shopping behaviour.

Consumer shopping behaviour is complex in the sense that the underlying behavioral process operates in continuous time but manifests itself in a series of discrete events, ie. purchases (Allison, 1984). Longitudinal panel data that supplies a complete record purchases on individuals, including information on their number, sequence and timing is better referred to as an 'event history' (Coleman, 1981). By the very nature of the behavioural process such 'event histories' generated from consumer panels, will consider a large number of events over a relatively short time. Methods of event history analysis are well suited to studies of dynamic behaviour and have been successfully applied in the biometric, sociometric and engineering literatures, although as yet, they have not been applied to examine consumer purchasing behaviour. Chapter 2 outlines various types on continuous–time models that have been used in empirical 'event history' analysis. This thesis adopts a continuous–time modelling approach to consumer shopping behaviour, utilizing SURVREG, a biometric–based software, and LIMDEP, an econometric–based package. Chapter 3 discusses the factors which are considered in a continous–time modelling approach of shopping behaviour and outlines the longitudinal panel data set used in this study.

The nature and importance of duration dependence in consumer shopping behaviour is examined in this thesis by successively incorporating elements of duration dependence into the range of event history models provided by both LIMDEP and SURVREG. The data set used in this research, an outline of the steps taken in the analysis as well as the suitability of the software packages for this investigation are also discussed in Chapter 3. Evidence as to the nature of duration dependence in consumer shopping behaviour is discussed in Chapter 4, and the empirical significance of duration dependence, in light of these results, is addressed in Chapter 5.

CHAPTER TWO

MODELLING APPROACHES TO CONSUMER PURCHASING BEHAVIOUR

Consumer behaviour involves the acquisition, management and utilization of goods and services and is but one facet of the total life of an individual. Analysis of consumer purchasing behaviour examines factors influencing people's behaviour in a buying situation. Consumer behaviour analysis has been a specialized field of systematic study since the 1960's (Mahatoo, 1985), reflecting both the expansion and increasing importance of consumer–oriented industries and the growth of buyer affluence (which, in turn has resulted in a virtual explosion in the number and variety of competing products, brands and markets). Analysis of consumer behaviour is fundamental to marketing strategies because consumer–oriented industries need to answer questions, such as: who buys, what is bought, and when and where purchasing occurs, in order to develop effective merchandising, advertising and locational campaigns and hence to make informed planning decisions. The need to understand consumers and how factors influencing purchasing behaviour interact has led to the development of various modelling approaches to consumer purchasing behaviour. These modelling approaches examine different aspects of behaviour to varying degrees of complexity and are outlined in this chapter.

Models of consumer purchasing behaviour attempt to describe the choice (or decision–making) processes of consumers. In general, these models contribute understanding of the effect various factors have on buying decisions, and in some cases, models have been operationalized, becoming predictive tools in marketing strategies (Fotheringham, 1988; Gollins, 1989; Jones & Simmons, 1987; Mahatoo, 1985; Moloney, 1989; Massy et al., 1970; Uncles, 1988). For example, Moloney (1989) analyzes the influence of competition, market share and the socio–economic characteristics of a buying population in a trade area model of a Miracle Food Mart store in Ontario. Once the store's customers are identified by a trade area index value, the retailer can assess customer needs and adjust product mix, pricing and management strategies (such as, store expansions, closings or hours of operation) accordingly, thereby better serving current patrons and attracting new customers to the store. Models also provide a framework for consumer behaviour analysis and are useful in describing the salient features of consumer behaviour data. Models of consumer behaviour may be classified as either deterministic or stochastic/probabilistic (Mahatoo, 1985; Massy et al., 1970). In other words, models may be constructed to include or not include probabilistic components. Moreover, the introduction of probabilistic components may occur as an integral part of model specification or may be included ex post facto, to account for discrepancies between actual (observed) behaviour and model predictions.

Deterministic consumer purchasing behaviour models are concerned with describing observed buying behaviour and aim to analyze the causal factors involved in purchasing decisions. Some deterministic models may be considered superficial as they attempt to relate a given factor (for example, advertising) with behaviour, without considering the causal process involved (for example, an individuals perception of what the advertisement contains) (Mahatoo, 1985). Others are more structurally integrated and comprehensive, seeking to analyze the processes behind the relationships, in order to provide insight into observed purchasing patterns. These integrative–comprehensive models of consumer purchasing behaviour are difficult to operationalize mathematically because the causal *linkages* between individual perceptions, preferences, motivations and purchasing decisions are not empirically observable (Johnston & Wrigley, 1981), and consequently, such models have remained essentially conceptual. These 'conceptual' models have largely developed within the behavioural sciences, notably psychology, sociology and anthropology and aim to identify the complex structure of buying decisions as well as the factors which govern (and may feed back into) individual purchasing patterns. Conceptual models may provide useful, theoretical frameworks upon which mathematical models can be built. Factors which influence consumer behaviour and three of the major contributions to the conceptual modelling approach are discussed further in Section 2.1.

Given the nature of behavioural processes, a mathematical model capable of making precise prediction of consumer purchasing behaviour would clearly be extremely complex. The data requirements for such a model would be enormous, and at the very least, would require information on the state of the consumer's memory as well as details of the environment in which a purchase was made (Massy et al., 1970). Therefore, it is necessary to make assumptions regarding the net effects of all factors not included in mathematical models of consumer purchasing behaviour. These assumptions are also known as *response uncertainty* (Massy et al., 1970) and may be formalized in the use of probabilistic components. If formalized, these models may be considered explicitly stochastic, ie., probabilistic components are specified as a distinct component of the model. In this case, specification may be achieved by assigning distributional forms to represent the assumptions made about consumer purchasing behaviour so that probabilistic components are assumed to follow a specified distributional form, such as a normally distributed error term. Alternatively, models can be implicitly stochastic in which behavioural assumptions are not represented in distributional forms but are simply assumptions about general behaviour which can be expressed in a mathematical relationship. For example, in Moloney's (1989) study, it is assumed that consumers prefer to shop at large stores that are nearby and this is expressed mathematically in a measure of store attractiveness: the square footage of floor space divided by a function of distance. This model may appear to be deterministic on the surface but the response uncertainty associated with the behavioural assumption is recognized as being a stochastic process.

Mathematical models of consumer purchasing behaviour (both explicitly and implicitly stochastic) may be divided into aggregate and disaggregate approaches. Aggregate models are based on general assumptions of behaviour and may be constructed directly with their own component of response uncertainty and applied to aggregate (ie. group) behaviour. Disaggregate models, on the other hand, are based on individual level assumptions. In other words, response uncertainty is postulated at the level of the individual and model estimates are couched in terms of the probability of an individual's behaviour occurring over a set of possible responses. For example, in a disaggregate model, it could be assumed that a particular individual may or may not visit the closest store, whereas in an aggregate model, this assumption may well translate into assuming that all individuals shop at the closest store.

Aggregate modelling approaches to consumer behaviour have dominated the geographical and marketing research literature and have been used to examine those aspects of consumer behaviour such as store choice and trip generation (Burnett, 1977; 1976; 1973; Fotheringham, 1989; 1988; 1986; Kau & Ehrenberg, 1988; Lerman, 1979; O'Kelly 1981; Preston & Takahashi, 1988; Recker & Kostyniuk, 1978; Wrigley & Dunn, 1988; Wrigley, 1980). An example of the aggregate modelling approach is found in Spatial Interaction Models which examine the flow patterns of consumers, travelling from an origin, i, to a destination, j. The number of consumers travelling from i to j is then used to establish statistically the relative importance of different store characteristics in attracting consumers. Mainly due to the increasingly competitive retail environment, consumer–oriented industries have begun to focus observation on specific 'consumer–types', 'honing in' on their attributes which, in turn, has resulted in the need to acquire data at the individual scale. Consequently, recent studies have begun to disaggregate consumer behaviour models by incorporating individual–specific purchasing characteristics, thereby capturing the influence of population heterogeneity (Broom & Wrigley, 1983; Jones & Zufryden, 1980; Wrigley & Dunn, 1985d). Section 2.2 discusses the main advancements in aggregate modelling approaches and outlines more recent attempts to disaggregate these models.

Disaggregate models make assumptions concerning individual choice decisions and have largely been developed in the micro–economic literature. A major branch of this approach may be called "discrete choice modelling" because studies examine choices made from a set of *discrete* alternatives. This approach is based upon random utility theory which assumes that individuals are rational persons who select the most beneficial alternative (the one with the highest utility value) from all available alternatives. "Discrete choice modelling" has traditionally been concerned with accounting for general purchasing patterns of behaviour of the *average* consumer, hence the goal of this approach is to quantify the relationship between an observed choice decision, and the variables associated with both the individual and the choice environment. The major developments of discrete choice modelling approaches are outlined in more detail in Section 2.3.

Typical discrete choice models study choice decisions made at given points in time, in other words, application is usually limited to analyzing static choice behaviour. Current research in discrete choice modelling is concerned with extending these models to examine the dynamic nature of behavioural choices (Fischer & Nijkamp, 1987; Haag, 1989; Haag & Weildlich, 1988). However, there has always existed a body of literature in market research and geographical literature which has considered the dynamic nature of behavioural processes. Explicitly stochastic disaggregate modelling approaches dominate this type of analysis and can be stated formally through the use of various types of feedback or adaptive–behaviour models; an example in the consumer behaviour context being the Linear Learning Model (Aaker & Jones, 1971; Burnett, 1977, 1976; Kuehn, 1962; Lilien, 1974). In their basic form, feedback/adaptive–behaviour models examine the influence of the most recent purchase on current choice decisions. Extensions of these models examine the influence of a series of recent choices and are described in Section 2.4. However, feedback or adaptive–behaviour models typically fail to consider the influence of the total history of consumer purchasing experiences. Continuous–time event history modelling approaches, on the other hand, consider purchase probabilities that result from an individual's entire past purchasing history thus incorporating the influence of time dependence on the behavioural process. Therefore, continuous–time event history models inherently consider the dynamic nature of consumer purchasing behaviour. Section 2.5 describes various types of continuous–time event history models which have been used in behavioural research and discusses developments made towards more generalized versions of these models.

2.1 Conceptual Modelling Approaches

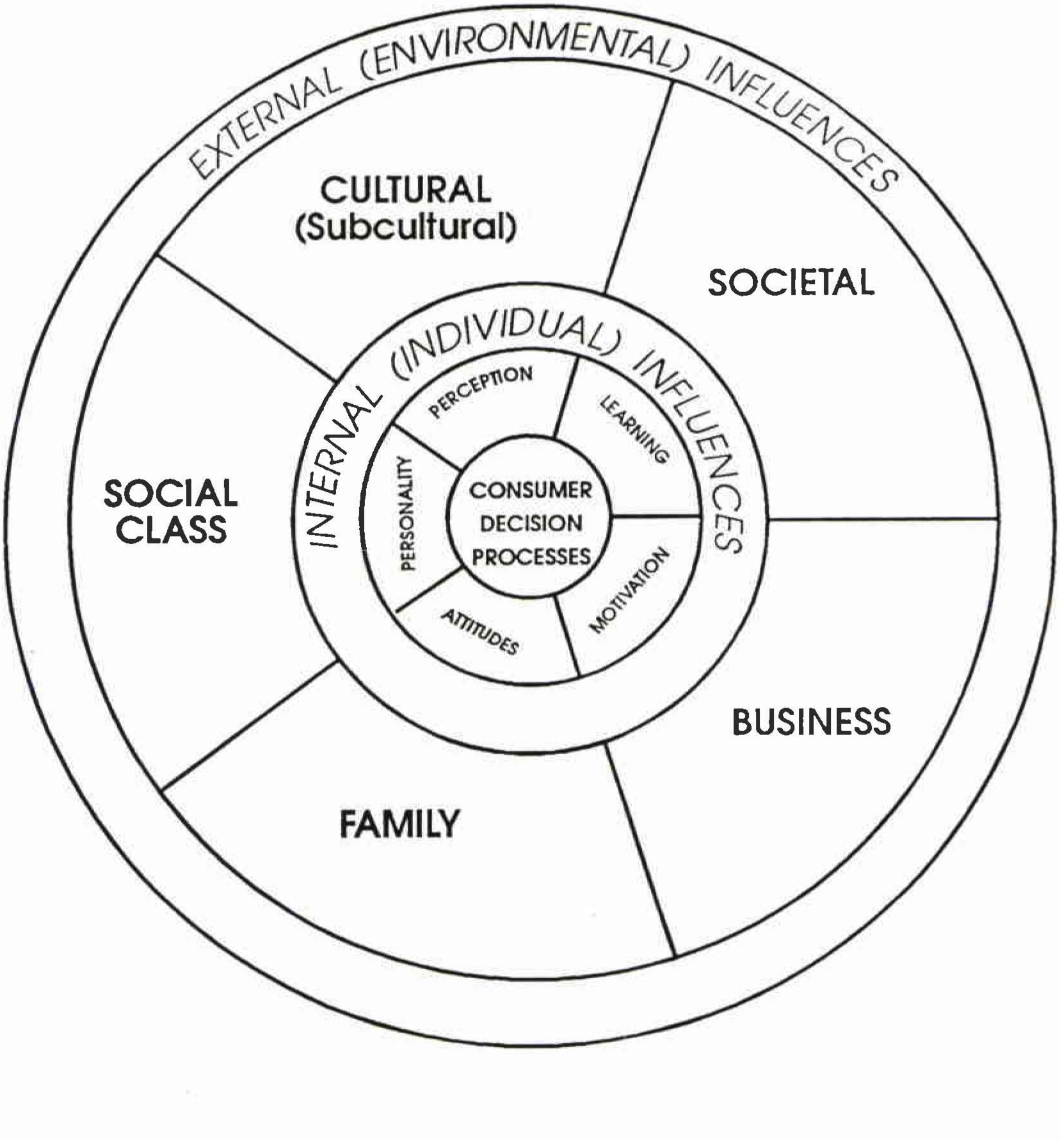
Conceptual modelling approaches to consumer purchasing behaviour view individual consumers as psychological entities operating within social environments. Within a conceptual modelling framework, purchase decisions are identified as complex processes which begin with a stimulus, such as a product and end with a response, the decision to purchase or not to purchase. Consumer choice processes involve a number of steps including: problem recognition (ie. deciding to purchase), information search and evaluation (ie. the search for a set of alternatives), and the subsequent decision between alternatives (ie. the purchase choice). A consumer's potential decision is influenced by both the technical aspects of the product itself and the total meaning (symbology) which the product carries (Kassarjian & Robertson, 1968; Kotler, 1968; Mahatoo, 1985; Schiffman & Kanuk, 1987). Symbology, in this context, deals with the image that a brand/product or store represents to the consumer and is an integral feature of purchasing stimulus. For example, most automobiles provide equally efficient transportation so the decision to purchase one car instead of another may well be made in terms of symbolic meaning. A Chrysler New Yorker symbolizes quality and prestige whereas a Ford Mustang Convertible 'means' youthfulness and sportiness; thus, a consumer's decision is based on the car whose brand image is most desired. In other words, consumer purchasing behaviour depends on an individual's perception of a product's ability to satisfy his/her needs and desires and this perception, in turn, is based on the life experiences of the individual.

In consumer purchasing, as in any choice situation, an individual is subject to a number of influences which determine the decision–making process. Figure 2.1.1 (page 27) is a simple model of consumer purchasing behaviour depicting two sets of influences involved in the consumer decision process: internal or individual influences and external or environmental influences. Internal influences include individual perceptions, motivations, attitudes, personality and knowledge. External or environmental influences entail the culture (or subculture), social groups, social class and family to which an individual belongs, as well as the influence of business.

2.1.1 Internal/Individual Influences

Among the internal influences, perception is concerned with information processing, that is, the way in which an individual comprehends and interprets

Figure 2.1.1: Factors influencing consumer decision processes



(source: Mahatoo, 1985:15)

exposure to a stimulus. How an individual perceives may be related to three factors: the source of the stimulus (which may be external, for example, a television advertisement, or internal, for example, an individual's hunger pains), the characteristics of the stimulus (the projected symbolism of the advertisement, or the intensity of the hunger pains), and the characteristics of the perceiver (the individual's needs, values, expectations, interests, etc...). However, information, although comprehended, may not be retained (and therefore acted upon) unless it is first accepted as conforming with the existing cognitions of the individual (Mahatoo, 1985; Schiffman & Kanuk, 1987). Thus the same stimulus can, and often is, perceived differently by different individuals. Since consumers act and react on the basis of their perceptions, buying decisions are affected by what an individual perceives to be so, rather than what actually is. Therefore, from the retailer's viewpoint, it is more important to understand consumer perceptions of the retail environment than consumer knowledge about the retail environment in order to determine more readily what influences consumer buying behaviour.

Consumer motivation is of central importance to consumer behaviour research since it concerns understanding the reasons why consumers behave as they do (Mahatoo, 1985). Motivation can be defined as the driving force (either conscious or subconscious) which impels individuals to act. The motivational state of an individual is the result of her/his subjective psychological state (ie. their needs, wants and desires) and may change with learning due to the input of new information. Furthermore, motivation comprises a significant part of an individual's personality. Motivation not only differs between individuals but observation of a particular individual's motivational state is attainable only if the consumer is conscious of his/her behaviour. In other words, motivation is interrelated with the other internal influences, influencing and being influenced by perception, knowledge and attitudes of the individual and is often an elusive and unobservable phenomena.

Consumer attitudes are an individual's general inclination, favorable or unfavorable, towards a given object (person or idea) such as, a product category, brand, service, advertisement, price or retailer. Attitudes are the outcome of psychological processes and can be important internal influences in the decision–making process. For example, how an individual feels about a particular brand will, for the most part, determine whether or not they choose that brand (LaBarbera & Mazursky, 1983; Mahatoo, 1985; Simonsen et al., 1988). Furthermore, attitudes can influence how an individual perceives an object, the kind of satisfaction sought by a consumer and may, in turn, be altered by her/his perceptions, motives and knowledge. Attitudes consist of three components: cognition (the beliefs an individual has about an object), affect (how the individual feels about the object), and action (whether or not the individual acts on those feelings) (Mahatoo, 1985; Schiffman & Kanuk, 1987). Creating or altering consumer attitudes is important to consumer–oriented industries, which typically attempt to assess market attitudes by conducting consumer surveys or by making inferences from observed choice behaviour. Consumer attitudes may be consistent with the observed behaviour it reflects but it may be a suspect assumption that all overt behaviour necessarily reveals attitude preference (Lawrence, 1966; Schiffman & Kanuk, 1987; Thrift, 1981).

Constraints surround individual choice. These constraints may be in terms of coupling constraints, like household interaction, or capability and authority constraints, like mode choice or employment, the latter often resulting in no choice exiting at all, irrespective of attitude preference. Attitude preference implicitly conveys the notion of underlying tastes that exist independently of constraints and, as such, is largely a theoretical notion. Choices, on the other hand, represent preference that is revealed but which operates within the confines of limitations (for example, spatial and temporal constraints). Therefore, preference is useful in identifying consumer attitudes only if observation of consumer behaviour considers the constraints that limit choice.

An individual's personality may be considered as the inner psychological characteristics that determine and reflect how individuals respond to their environment. Inner characteristics concern those specific qualities, traits, factors, attributes and mannerisms which distinguish one individual from another. Personality can be used to characterize individuals because it summarizes the perceptions, motivations, attitudes and knowledge which an individual holds. In terms of consumer behaviour, personality represents individuality and results in a heterogeneous consumer population. By assuming that consumers make purchase decisions which, in part, reflect their personalities, retailers can attempt to isolate personality traits of population segments and develop marketing strategies which will target and attract them as customers. For example, the field of geodemographic marketing capitalizes on this notion by identifying and categorizing consumers who share similar personalities and lifestyles. This information is used to define consumer profiles of geographic areas and then promotional campaigns are directed at these particular 'clusters' of consumers.

Consumer learning is a process by which individuals acquire the purchase and consumption knowledge and experience that they apply to future behaviour. Learning involves the establishment of connections between stimuli (for example, a product) and the cues which represent them (for example, the name colour and symbolism of the product) on the one hand, and consumer preference and response on the other. One of the major developments in consumer behaviour research has been the realization that memory and the decision–making process interact (Burnett, 1973; LaBarbera & Mazursky, 1983; Mahatoo, 1985; Park et al., 1989; Schiffman & Kanuk, 1987; Simonsen et al., 1988). Learning continually evolves and changes as a result of newly acquired information, actual experience and post–purchase evaluation and consequently, forms knowledge. Experience and knowledge create a foundation upon which subsequent judgments and decisions are made. For example, in their empirical study of how brand search is affected by prior beliefs and knowledge, Simonsen et al. (1988) found that individuals use prior knowledge to ease their choice processing task by focusing initially on the more attractive brands and only later sampling information on less attractive brands. What consumers learn depends on how they perceive; how much they learn and how they respond is influenced by their motivations, attitudes and personality. Since learning is a selective process which cannot be directly observed, retailers must infer how and what consumers learn by examining buying patterns, the ways in which consumers have been influenced in the past, and by analyzing the formation of brand/store concepts.

The internal influences involved in consumer decision–making processes include: the way in which information is received and interpreted (perception), how it is remembered (learning), the needs and desires which direct the purchase (motivation), the individual's predisposition to a purchase choice (attitude), and the behavioural tendencies of the individual (personality). All of these factors govern individual behaviour in a purchase decision and their influence affects different individuals differently. Internal factors are also contingent on one another and may be reformulated as knowledge is acquired, however, one internal influence may dominate a consumer's choice in a given buying situation. For example, Park et al. (1989) examined the effects of situational factors on grocery shopping behaviour and found that the primary influence affecting failure to make *intended* purchases was due to a consumer's perception of a time pressure existing while shopping in the store. Since the products were intended to be bought the motivation to purchase, the attitude towards the product and the knowledge about the product had already been considered by the individual, leaving the buying trip outcome to be governed by the consumer's perception of a time pressure. Time pressure is an individual's interpretation of the time available for shopping (Park et al., 1989) and thus represents an internal influence on the purchase decision–making process. However, time pressure is also a situational factor which influences purchasing behaviour as it, in part, creates the environment in which buying occurs.

2.1.2 External/Environmental Influences

Situational factors such as, store layout, store knowledge and the time available for shopping, may be considered as environmental influences on purchasing behaviour since they direct the outcome of in–store consumer decision–making processes. Beyond these situational forces are other, more pervasive, environmental factors which influence the behaviour of consumers. As depicted in Figure 2.1.1. (page 27) these external (or environmental) influences represent social forces which dictate the purchase environment. While these external influences can be considered as situational factors, since they direct individual decisions, they extend beyond a particular shopping incident to involve influences on the buying behaviour of individuals that live in a consumer society.

Culture (of which subculture is a part) provides the broadest external influence on consumer purchasing behaviour (Mahatoo, 1985; Schiffman & Kanuk, 1987). Culture affects decision–making processes by regulating the consumption behaviour of members of a society who share learned attitudes, needs, values, customs and orientations. Culture supplies a society with a distinctive character and personality, and for consumer's, culture provides usual and acceptable ways of behaving. Culture is also dynamic and must continually evolve if it is to function in the best interest of a society. Therefore, retailers must monitor socio–cultural environments to develop successful marketing and advertising campaigns which reflect the needs and preferences of different consumers. Cultural traits can also be used to provide a basis for segmenting consumer markets and thus provide retailers with a basis for devising target marketing strategies, aimed at particular sub–groups or subcultures.

In general terms, a society can be defined as a system of community life in which individuals interact and form routinized and regulatory association for mutual benefit. Society provides an organized frame of reference for behaviour through order, governing rules, and a group belief system and results in the formation of culture. As with culture, society influences individual attitudes, customs, orientations, etc... thus affecting the individual/internal influences which govern the decision–making process. As a result of societal interaction, individuals form social groups or sub–sets of society which act as reference groups and with whom an individual identifies him/herself. These social or reference groups may be broadly circumscribed to include both direct and indirect group influences; the former including persons with whom an individual has face–to–face interaction (family, peers, shopkeepers); the latter describing groups with which an individual associates indirectly (celebrities, corporate and political leaders). Identification of social group needs and values enables retailers and marketers to provide appropriate goods and services to accommodate consumer demand.

Social class is the stratification of members of a society into a hierarchy of distinct status groups. Members of the same social class share the same status by possessing commonalty in certain attitudes, values and lifestyles whereas members of other social classes have either more or less status. Social class can be viewed as an indirect reference group in that it provides non–personalized social norms which can affect individual attitudes and behaviour. Social class also serves as a direct reference group because it is most likely that individuals within a particular class will turn to members of the same class for appropriate behavioural clues (Mahatoo, 1985; Schiffman & Kanuk, 1987). In consumer behaviour studies, social class is most often defined in terms of socio–economic or demographic variables which serve as expressions for social status such as, occupation, income and educational attainment. These variables may then be used in model applications to identify and account for individual differences in behavioural variation, thereby providing a measure of the differences which occur between consumers. Furthermore, members sharing the same social class tend to locate in proximity to one another in distinct areas spatially segregated from other social classes, the classic example being the uptown/high class population versus the downtown/lower class (or railroad) community. Social class strata provide a natural basis for market segmentation, enabling effective product tailoring, channeling of distribution patterns and the delivery of promotional messages which are appropriate to the interests and needs of specific social groups.

Family has a tremendous influence on consumer decision–making processes as it is the basic social group to which an individual belongs. Families and households are often treated as synonymous in the consumer behaviour literature; however, not all households are families. Traditionally, family is defined as two or more persons related by blood, marriage or adoption and who reside together (Schiffman & Kanuk, 1987). Households, on the other hand, are simply individuals who reside together and include unmarried couples, family friends, roommates or boarders. In either case, the family/household unit forms the basic social group, interacting with each other to provide economic well–being, emotional support and suitable lifestyles. Family provides early childhood learning about products, providing the opportunity for product exposure and repetition, establishing acquisition patterns for goods and services and is crucial in the formation of an individual's personality, values, attitudes preferences and habits. Central to the study of consumer behaviour is the role of family in consumer socialization: the process by which children acquire the skills, attitudes and knowledge necessary to function as consumers. Consumer socialization has two distinct components: those directly related to consumption (such as, learning about budgeting, pricing and shopping); and those indirectly related to consumption (ie. the underlying motivations which govern and spur individuals to buy). It is the indirect component of consumer socialization that is of prime interest to retailers, marketers and academics who want to understand consumer purchasing behaviour.

Consumers are also influenced by a number of external influences which are generated by business organizations including retail store strategies, merchandising campaigns, marketing communications and distribution schemes. Successful business–oriented strategies must have thorough, explicit understanding of what makes consumers buy, what needs consumers are trying to fulfill and what outside influences affect buying choices. Furthermore, the business environment is rapidly changing, current marketing concepts are concerned with determining the needs and wants of specific target markets and delivering the desired satisfaction better than the competition. Only by understanding the nature of consumer behaviour can business organizations design effective campaigns which will favorably influence consumer decisions.

Figure 2.1.1 illustrates the pervasive nature of external influences, including cultural, social and business influences, on the internal factors involved in the decision–making process. However, it is the combined effect of both sets of influences which ultimately govern the purchase process. In any buying situation the stimulus to purchase is defined by commercial retailing and marketing efforts as well as non–commercial influences which are dictated by the consumer's internal characteristics and her/his social environment. Business creates the climate in which consumers shop and is successful when the goods and services that are offered are appropriate to the needs of the market. Definition of this need is determined by individual motives, personality, life–style, cultural norms, values and reference groups which, in turn, are influenced by business, family, society and experience. Through social interaction, individuals define their own identity, values and attitudes by relating and assessing the behaviour of others. The decision–making process itself is influenced by a consumer's own sociologically defined psychological fields which affect the ability to recognize a need, the pre–purchase search for information and the evaluation of alternatives. The purchase decision includes the actual purchase (or non–purchase) and the post–purchase evaluation, both of which are subject to selective perception (influenced by both psychological and social factors). Pre– and post–purchase evaluation then feedback into the consumer's psychological field in the form of experience and serve to influence future decision processing.

Central to consumer behaviour studies is understanding how these internal and external factors interact to bring about a particular behaviour and to identify the reasons for behavioural variation across individuals. One way to synthesize and delineate the complex relationships among these influences is to develop models which clarify the more important factors involved in purchase decision processes. Simple models allow researchers to see more clearly what is going on, less simple ones help us understand, even less simple models allow prediction of what will likely happen, and the most complex ones are able to describe, explain and predict behaviour so that control of circumstances and their outcomes becomes possible (Mahatoo, 1985). The final form and usefulness of *any* model depends on the precision of the theories, assumptions and observation from which the model is built.

Conceptual models of consumer behaviour are essentially comprehensive, descriptive models which possess some explanatory capabilities and to a large extent are elaborate flow charts which seek to explain decision–making behaviour.

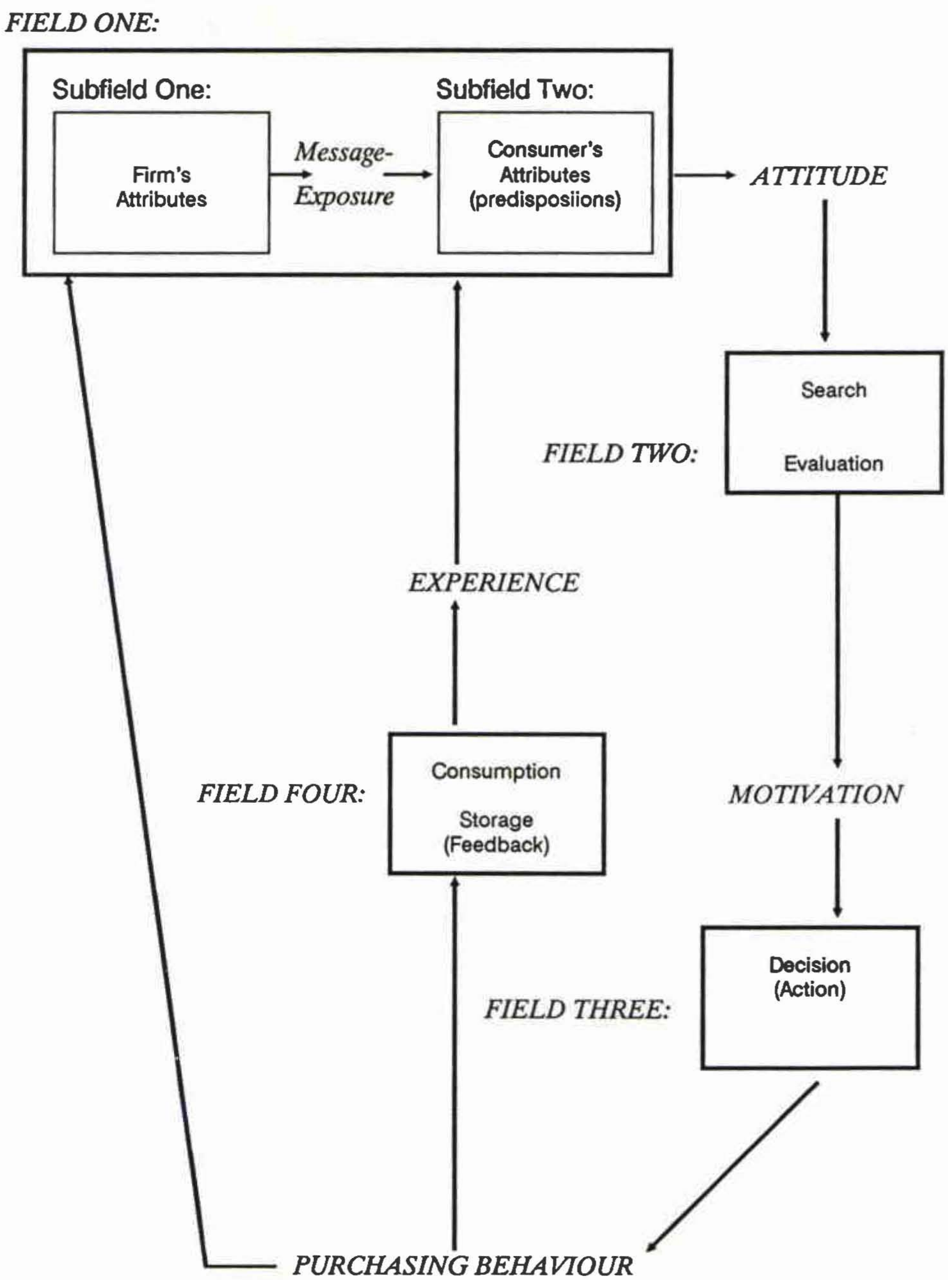
Conceptual models attempt to integrate information known about consumer behaviour and do not consider all the possible variables that might affect consumer actions, rather, each model represents a particular perspective. Theoretical perspectives that have been used in consumer studies are reviewed elsewhere (for example, see Kassarjian & Robertson, 1968) and will not be discussed here. Suffice to say that the comprehensiveness of conceptual models lies in the depth of the perspective presented and in the specification of the relationships among variables. Likely the most important role of the conceptual modelling approach is to generate researchable hypotheses about behaviour and to provide insight into gaps which exist in current knowledge and understanding of consumers.

2.1.3 The Niscosia Model

Nicosia (1966) is responsible for one of the earliest attempts to develop a conceptually integrative, comprehensive model of consumer purchasing behaviour. A distinctive feature of Niscosia's approach is a shift in emphasis away from the purchase act itself toward the purchasing process, consisting of the act as well as the steps taken both preceding and following it. The focus of the model is on the interactive relationship between the firm and potential consumers, wherein the firm communicates with consumers through marketing messages (for example, advertisements) and consumers communicate with firms via their purchase responses. In its complete form, Niscosia's (1966) model is an elaborate computer flowchart of decision–making sequences in which consumers are assumed to actively seek to satisfy certain goals through a rational process, reducing a number of choice alternatives down to a final selection.

Figure 2.1.2 (page 38) is a summary flowchart of Niscosia's original model which highlights the main features of his approach. The model is expressed as a series of fields, each one serving as output from a preceding field as well as input to

Figure 2.1.2: The Niscosia model of the consumer decision process



(based on: Niscosia, 1966:56)

a succeeding field. The first field is divided into two sub–fields and describes the variables and mechanisms which may lead to the formation of attitudes regarding a particular brand or product. Subfield one concerns the firm's marketing environment and communication efforts which transmit messages to individuals in the hope of influencing their attitudes. The second subfield specifies various consumer characteristics (such as, personality, pre–disposition and experience) that mediate reception of the firms promotional messages. The interaction between the two sub–fields results in an attitude toward the product/brand based on the consumer's interpretation of the message. The second and third fields of the model consider the variables and mechanisms which may intervene over the time between the formation of consumer attitude and the purchase act itself. The second field deals with the transformation of an attitude into a motivation toward the advertised product/brand via search and evaluation of comparable alternatives. The output of field two is the motivation to purchase but, evaluation can also lead to rejection of a firm's message, something not considered in the Niscosia model. The Niscosia model considers only a positive response, ie., the purchase of the product/brand from a specific retailer, resulting from motivation, and this output is specified in field three. The fourth field considers the crucial influence of feedback from the purchase experience on future decision–making and is expressed in two forms. One form of feedback is in the sales data which relates the purchase act to the decision mechanisms of the firm (subfield one of field one), the second form of feedback is in terms of the consumer's experience with the purchase (subfield two, field one). Experience affects the consumers predisposition to the product/brand therefore, attitudes are modified or reinforced in light of the buying experience which consequently, influence the way an individual will interpret future messages from the firm.

Niscosia's (1966) model portrays a 'funnelling–type' decision process wherein emphasis is placed on the idea that consumer predispositions move from generality (very broad intentions) through search and evaluation of alternatives, culminating in the selection a product/brand. However, this type of decision–making process may be too reliant on over–rational consumers and is unlikely to hold when purchasing decisions of different individuals is examined. At the very least, funnel–type decision–making is more relevant to infrequently purchased high–cost products than it is to frequently purchased low–cost products, such as groceries (the latter comprising the bulk of consumer purchases) (Lunn, 1974; Mahatoo, 1985). Niscosia's (1966) model concentrates on product and brand purchases although he does recognize the influence of store choice on buying behaviour. Store attributes are ascribed to influence the conversion of motivation to purchase to a purchase act. Niscosia reasons that because different stores possess different store attributes the influence of store choice varies, being either a constraint (by not stocking the preferred brand) or a filter (which may enhance or detour the action taken toward the preferred brand). What constitutes store attributes is not clear, however, Niscosia's (1966) discussion implies that these attributes refer to in–store features (for example, window displays, price specials and sales clerks) and not the spatial constraint of store location (which is often a primary determinant of store choice) (Carman, 1970; Engel et al., 1986). Niscosia (1966) describes the influence of time dependence on decision–making processes in terms of the rate of change in consumer attitudes and purchases however, the duration between consumption and re–purchase is neglected, a dependence which is likely the major driving force behind purchasing and repurchasing rates. The social and physical purchasing environment is regarded as dynamic, changing over time due to experience as new and different messages come from the firm and changes with respect to individual motivation.

Prominent among criticism of the Niscosia model is that his definitions of attitude, motivation and the interrelationships among variables and mechanisms are ambiguous (Lunn, 1974; Mahatoo, 1985). Furthermore, Niscosia's attempts to formalize his model mathematically (see Niscosia, 1966: chpt. 7) is "prematurely ambitious" (Lunn, 1974:43) largely because of the generality of the terms used in formulating the model and the inability to empirically observe many of the model variables. Though Niscosia is criticized for achieving little in advancing understanding of consumer behaviour (Mahatoo, 1985), his model does provide an invaluable pioneering contribution to consumer behaviour research.

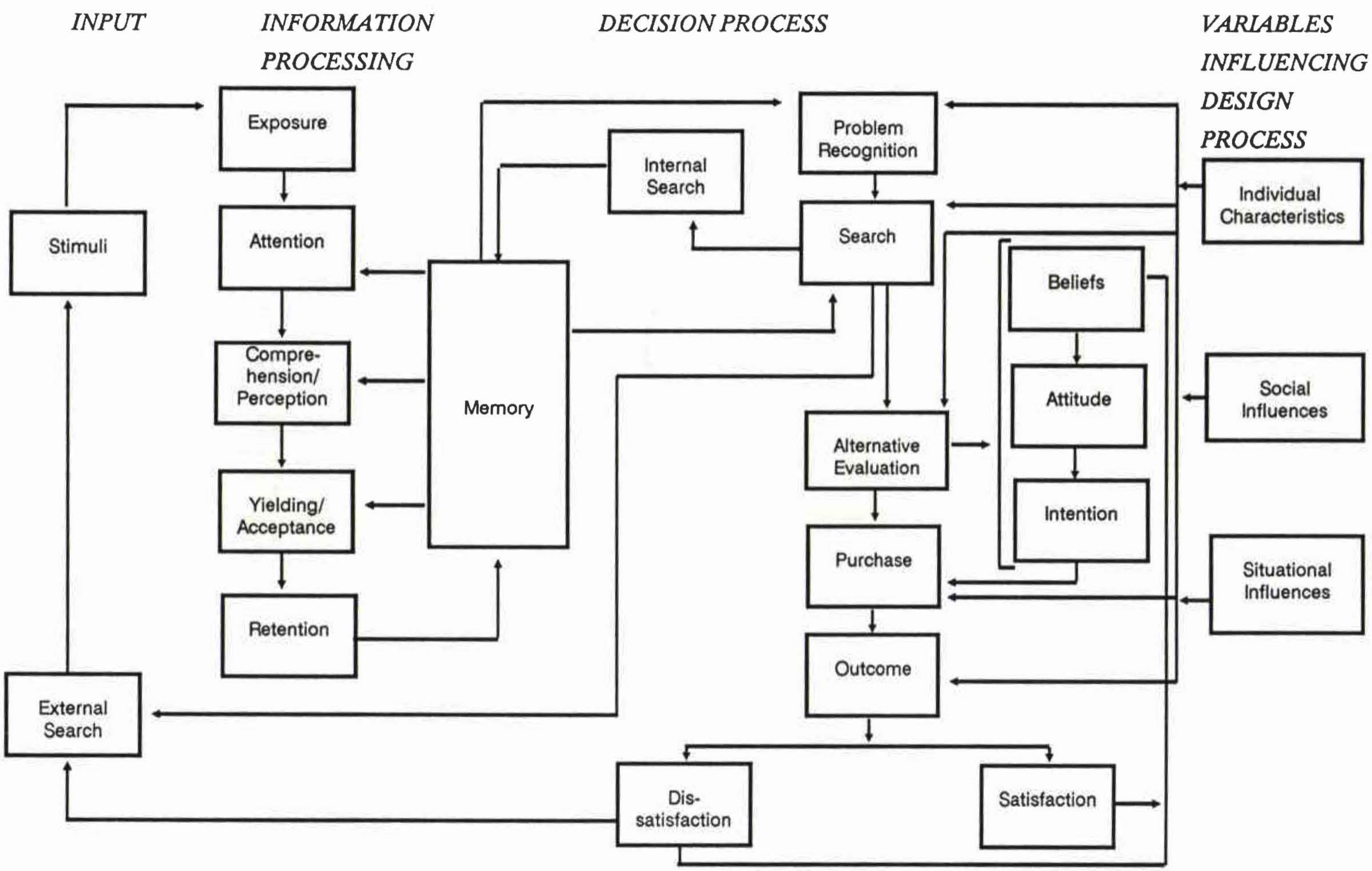
2.1.4 The Engel, Kollat and Blackwell Model

The Engel, Kollat and Blackwell (EKB) model was originally designed to serve as a framework for organizing consumer behaviour knowledge and since the original publication the model has undergone a number of revisions, aimed at improving clarity and descriptive ability. The model is built around stages of decision–making and, like the Niscosia model, the EKB model portrays a series of processes whereby products are sought and evaluated in terms of consumer goals and future purchases are influenced by past experience. Unlike Niscosia, Engel et al. (1986) view consumer goals as the result of interaction between stimuli which may be either endogenous (internal) or exogenous (external) to the individual. Feedback in the EKB model explicitly specifies post–purchase feedback as either dissonance (thereby initiating search anew) or satisfaction (which reinforces beliefs, attitudes and intentions). Motivation in Niscosia's model is equivalent to intention in the EKB model, however, unlike the Niscosia model, intention is not considered static (ie. does not always result in a positive response/purchase). Intention in the EKB model may change as a result of unanticipated and anticipated circumstances (ie. situational factors) and the degree of this change is considered time dependent; the general rule being that the shorter the time interval the stronger the intention–observed behavior relationship (Engel et al., 1986).

Figure 2.1.3 (page 43) presents the most recent version the the EKB model which consists of four stages: the decision process, information input, information processing and variables of the decision–making process. The central focus of the model is on the decision process stage whereas in the Niscosia model, focus is on the interrelationship of the firm and the consumer. The decision process stage of the EKB model (a.k.a. the central control unit) is comprised of: problem recognition, search and evaluation of alternatives (during which beliefs may form attitudes thus can influence purchase intention), the purchase act and the outcome of the buying decision. The relative attention given to each of these components is flexible and depends on how extensive the problem solving task is. For example, in 'extended' problem–solving the consumer is assumed to pass through all five components of the decision process; in a 'routine' problem–solving task the consumer is assumed not to experience external search and alternative evaluation (Engel et al., 1986; Lunn, 1974).

Impact of the firm on the consumer is considered in the input stage of the EKB model and consists of information from both (external) marketing and (external or internal) non–marketing sources. Information input may arouse the decision–making process, however, Engel et al. (1986) recognize that even if the system is active the individual does not necessarily perceive all the stimuli to which she/he is exposed. After the input stage information passes through the consumer's memory which filters the information and retains it only if it is relevant to his/her current motives and consistent with stored knowledge and expectations. Memory also affects and is affected by information processing, the third stage in the decision–making process. As indicated in Figure 2.1.3 the information processing section of the model consists of a consumer's exposure, attention, comprehension/perception, yielding/acceptance and retention of incoming

Figure 2.1.3: The EKB model of consumer behaviour



(source: Engel et al., 1986:35)

information from the input stage. Therefore, before a message can be utilized by a consumer, she/he must: (1) be exposed to it, (2) allocate information–processing capacity to the incoming message, (3) interpret the stimulus, (4) be persuaded by it, and (5) retain the message by transferring input information to long–term memory (Schiffman & Kanuk, 1987). Thereafter, information passes through all five components of the information process stage and becomes experience and knowledge, both of which play significant roles in the model's decision process stage and are themselves added to by the outcome of the choice.

The influence of internal/individual and external/environmental influences on the formation of consumer goals and the decision process is recognized in the variables influencing the decision process stage of the model (see Figure 2.1.3). Individual characteristics include motives, values, lifestyle and personality, while social influences refer to culture, reference groups and family. Situational factors (for example, financial constraints or time pressure) are also considered and all of these variables are reasoned to affect the five areas of the decision process stage. The relationships among different variables of the EKB model are specified (verbally) in a 'formal statement' of the model, consisting of a series of definitions and equations devised to permit comparison with other models (see Engel et al., 1986 for details). Due to the symbolic logic of the formal statement, the EKB model could be empirically testable but as yet, this has not successfully been achieved. The merit of the model lies in its simplicity and although it is less detailed than Niscosia's model (see Lunn, 1974) it displays more flexibility and adaptability. As with the Niscosia model, the EKB model focuses on product choice and while the influence of store choice is discussed in the text (see Engel et al., 1986: chpt. 19) the affects of location on decision–making behaviour are not addressed in the model per se. The EKB is criticized for overemphasizing determinism in consumer behaviour by specifying highly rational search and evaluation processes.

The model is accused of making buyer behaviour look too mechanical and devoid of complexity, however, as Mahatoo (1985:400) poignantly notes: this is "perhaps unfair because the objective of model–building is to simplify in order to increase comprehensibility", a trade–off common in all models of consumer behaviour.

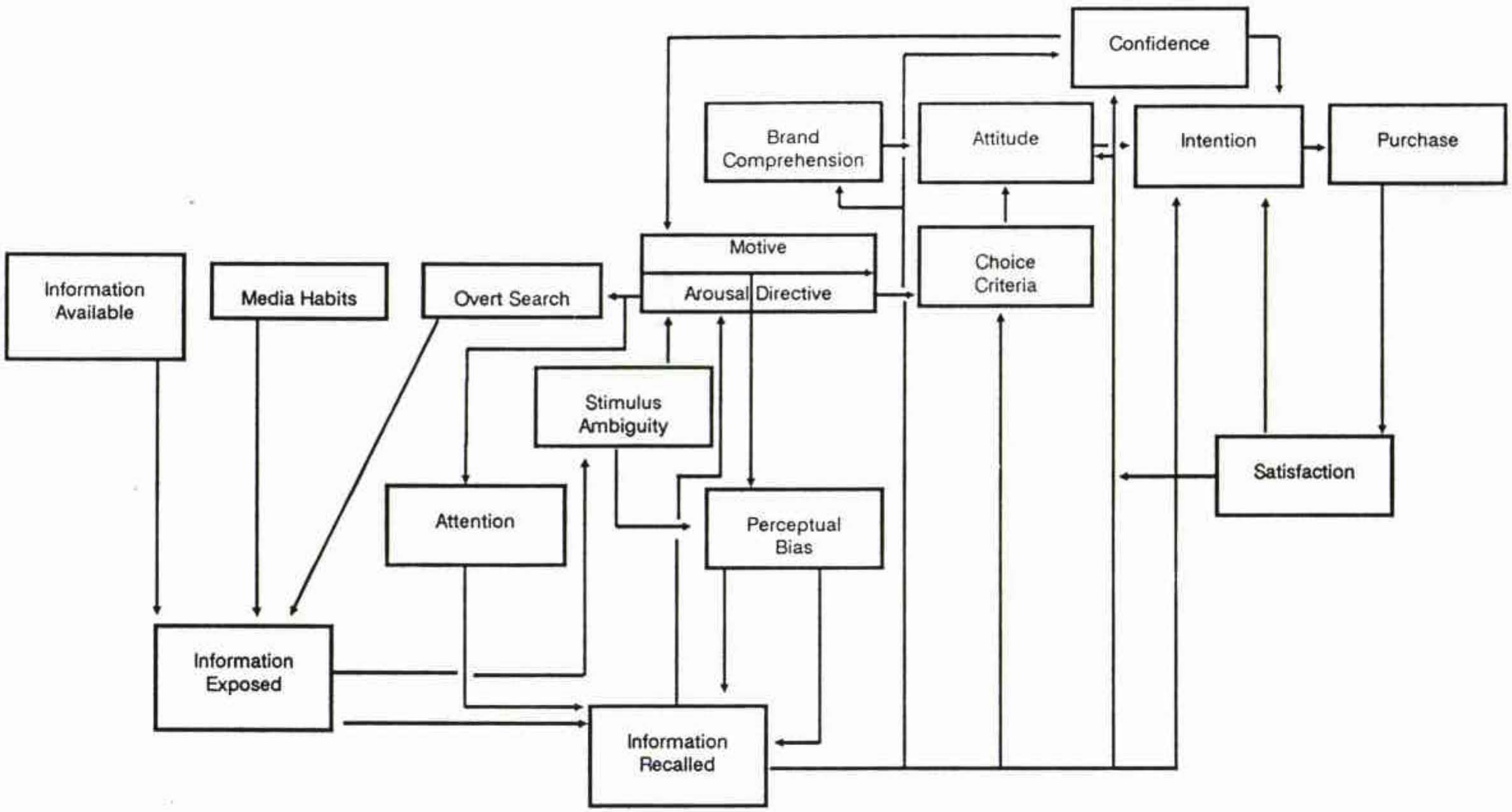
2.1.5 The Howard–Sheth Model

The Howard–Sheth (H–S) model of buyer behaviour is praised as being the most thorough, comprehensive and well–articulated conceptual model published to date (Lunn, 1974; Mahatoo, 1985). Unlike other conceptual modelling approaches to consumer behaviour, Howard and Sheth focus on the element of repeat buying in their model theory which incorporates the dynamics of purchasing behaviour (see Howard & Sheth, 1968 for details). The original model proposed by Howard was later modified in collaboration with Sheth, producing a more refined model intended mainly to explain brand choice behaviour. The model is based on learning theory and examines the dynamics of a rational buying process by making a distinction between three levels of learning (or stages in decision–making): extended, limited and routinized problem–solving. Extended problem–solving occurs when the buyer's knowledge and beliefs about brands is very limited or nonexistent thus, as with the EKB model, the consumer actively seeks for information on alternative brand choices. A limited problem–solving task applies when brand knowledge and beliefs are only partially established (for example, the situation in which a consumer is confronted with an unfamiliar brand in a familiar product class) hence some comparative information is sought although choice criteria are fairly well–defined. Howard and Sheth's routinized problem–solving definition is equivalent to that of the EKB model; response behaviour is well–established, thereby making search and evaluation procedures unnecessary and predisposition to a particular brand (ie. brand loyalty) is often expected. This distinction between different problem–solving tasks is in accord with the rational accounts of individual decision–making proposed by Engel et al. and Niscosia. However, it is important to note that the decision process can occur at the conscious or subconscious level therefore, this distinction between different types of tasks may not always appear to be rational to an outside observer. Consequently, Howard and Sheth (1968) argue that indication of the type of problem–solving task is represented by the length of time taken to make a purchase choice. Extended tasks take a long time, requiring a great deal of information prior to purchase, routinized problem–solving occurs quickly, needing little or no information and limited task decisions occur in a moderate amount of time.

Figure 2.1.4 (page 47) illustrates a simplified (1974) version of the H–S model which is based on an elaborate processing mechanism that shares similarity with the EKB model. The H–S model consists of four major sets of variables: inputs, perceptual and learning constructs, outputs and exogenous variables (the latter not depicted in Figure 2.1.4). Input variables correspond to all the information to which an individual is exposed and is a function of the consumer's media habits and/or specific search behaviour. Howard and Sheth make a distinction between different types of information input: significative stimuli (the physical characteristics of the brand, such as price and availability), symbolic stimuli (linguistic or pictorial representation of brand attributes from commercial sources) and social stimuli (provided by family, reference groups and social class, the most obvious being word–of–mouth communication) (Howard & Sheth, 1968; Schiffman & Kanuk, 1987). Stimuli input is processed and stored through interaction with a series of hypothetical constructs that are internalized by the consumer, who reacts to the stimuli immediately, or later.

Perceptual and learning constructs are central to the H–S model and are composed of psychological variables which are assumed to be operating when a

Figure 2.1.4: The Howard–Sheth model of buyer behaviour, 1974 version



(source: Mahatoo, 1985:401)

consumer contemplates a decision. Perceptual constructs serve the function of information processing and include overt search, stimulus ambiguity, attention and perceptual bias variables. For example, stimulus ambiguity occurs when a consumer is unclear about the meaning of symbolic stimuli and results in the individual undertaking further search or forming a perceptual bias (ie. retention of distorted information). Therefore, perceptual phenomena create change in the quality or quantity of information received by the consumer, who either ignores it, sees it attentively, or imagines something not present in reality (Howard & Sheth, 1968). Learning constructs, on the other hand, serve the function of concept formation and are labelled as motives, brand comprehension, attitude, choice criteria, confidence and intention. Recalled (ie. learned and retained) information may stimulate motives which rouse the individual to pay attention to stimuli, attention itself being an active selection procedure. Once motives are established and the type of problem–solving task is identified, the consumer either initiates search for additional information or evaluates known choice criteria. What the individual knows and feels about the brand (ie. brand confidence) is a function of previous experience which interacts with new information, resulting in the formation of a brand attitude. Brand attitude directs the purchase act because it forms the basis for the intention (ie. motive) to purchase. Hence the output variables of the hypothetical constructs include brand attitude and purchase intention, both of which direct the purchase act. Howard and Sheth (1968) view the purchase act itself as a manifestation of the buyer's predisposition combined with any constraints that may be present.

Satisfaction, as a purchase outcome, refers to the degree of congruence between the actual consequences of the purchase and consumption and the expectations the consumer held at the time of purchase. Howard and Sheth (1968) view satisfaction as both an output of the decision–making process and a learning construct, constituting experience which dictates whether or not a repeat purchase will occur. However, the relationship between satisfaction and repeat purchase is more complex than simply the purchase being more or less than what the consumer expected. LaBarbera and Mazursky (1983) empirically examined the role of satisfaction on repeat purchasing behaviour for 87 consumers buying grocery products. From their questionnaire data they found that the repurchase of a given brand is influenced by intention and intention is mediated by satisfaction. However, they also found that despite a high degree of satisfaction with current consumption, situational factors (such as coupons and sales) and prior purchasing experience may dictate a purchase act (see LaBarbera & Mazursky, 1983). Furthermore, switching behaviour was found to be more sensitive to dissatisfaction although, the direct relationship was not very substantial. They conclude that the timing of observation measurement largely determines the role of satisfaction in repeat purchasing behaviour because the highest construct validity of satisfaction is a measure of the immediate past, and the longer the time interval between purchases the more likely satisfaction will decay to attitude (LaBarbera & Mazursky, 1983).

As in the previously described models, the Howard–Sheth model focuses on the behaviour of individual consumers who are goal–oriented and rational, actively seeking, selecting and processing information during the decision–making process. In all three models individuals are believed to develop criteria for judging brands and products and for devising strategies that are used to selectively deal with information input. Like the Niscosia and EKB models, the H–S model emphasizes the dynamic influence of satisfaction with the purchase experience, generating an adaptation level or serving as an anchor for subsequent judgments. Satisfaction as feedback influences individual predispositions, brand attitude and confidence and if retained, can affect future decision–making behaviour (Howard & Sheth, 1968). It is important to note that most discussion regarding the H–S model applies implicitly to limited problem–solving because the role of feedback from attitude, confidence and product class would not be as influential in extended problem–solving (Mahatoo, 1985).

Personality, culture, social class, reference groups, financial status, time pressure and the importance (or value) of the purchase to the consumer are considered as exogenous variables in the H–S model and encompass the anticipated and unanticipated circumstances described by Engel et al. (1986). Howard and Sheth's distinction between exogenous and endogenous variables appears to confuse the relationship between exogenous/endogenous versus past experience/situational factors. They argue that exogenous variables account for past effects that are not related to a specific decision, whereas endogenous variables comprise effects that currently and directly influence the consumer's observed buying behaviour (Howard & Sheth, 1968). Conventionally, both exogenous and endogenous variables are viewed as influencing a specific buying decision, not just the endogenous factors as Howard and Sheth imply. Endogenous factors comprise characteristics arising from previous decisions (ie. past experience). Exogenous variables, on the other hand, represent individual differences among buyers and situational factors which affect the purchase choice. Endogenous variables for a current choice are causally related to the exogenous variables of a previous choice and may result in a spurious association between the exogenous and endogenous variables which currently influence behaviour (Davies & Pickles, 1985). For example, a strong association may be expected between the endogenous variable 'previous store visited' and the exogenous variable 'current car availability' in a study of store switching behaviour. This relationship reflects the influence of car availability on store shopping behaviour during a previous visit but also recognizes that, in general, car availability may effect the current decision to re–visit that particular store.

Howard and Sheth specify the relationship among exogenous variables in a formal statement of the model, composed of twelve equations which seek to indicate (verbally) the relationships among variables and developed to act as a foundation for empirical testing of the model. Farley & Ring (1974) attempt to derive an empirical version of the H–S model and while their results provide some support for the models theoretical constructs, they conclude that difficulty lies in combining the conceptual sofistication of the model with the methodological precision needed to adequately measure data (see Farley & Ring, 1974 for details). This methodological difficulty however, may in part, result from Howard and Sheth's conceptual distinction between exogenous and endogenous variables. Attempts to quantify the H–S model are difficult because of its indistinct model constructs which, when operationalized, lead to inappropriate specification of the relationship among variables. Moreover, quantification of any conceptual model is problematic since the variables are difficult to measure with any degree of accuracy and because the relationships between variables is unlikely to be empirically observable (for example, the relationship between motivation, attitude preference, constraints and revealed choice) and therefore, are not directly translatable to mathematical models due to their comprehensive and complex theoretical foundations. In fact, it is a questionable practice to operationalize these models at all since human decisions are not made in this elevated realm of theory but are made in practical situations although, the theoretical logic does apply because it is played out in practice (Thrift, 1981). The notion that behavioural models must make simplifying assumptions concerning consumer decision–making is not at issue. What is at issue is how far assumptions can go before they become inaccurate statements of empirically observed consumer behaviour.

Generally, conceptual models focus on the determinants of the decision to buy and the factors which result from choices. Recurrent themes in the conceptual approach to consumer behaviour includes the influence of individual cognitive structure on product or brand choice, the importance of learning theory, information processing capabilities of consumers and the influence of group dynamics on individuals. Conceptual models are essentially normative models in which some of the sub–model processes utilize information from empirical behavioural research (Shepard & Thomas, 1980). Consequently, these models often over–simplify the type and direction of the relationships between variables involved in consumer decision–making by assuming linearity and imposing unidirectional causality. Empirical observation however, is crucial to understanding consumer purchasing patterns and, unlike conceptual models, empirically–based approaches result in testable decision–making models. Ehrenberg (1972) expresses this lack of empirically–based theory in Howard and Sheth's conceptual model formulation, commenting that if the model is stripped of its mathematics (ie. formal statement) and assumptions, the remaining theory does not contain any generalizable knowledge of consumer behaviour. The operational difficulty often associated with conceptual models limits their empirical testability and while these models may provide insight to the decision–making process, there is a need to first understand *how* consumers buy before the reasons *why* people buy can be successfully addressed.

2.1.6 Sources of Consumer Behaviour Variation

Sources of consumer behaviour variation described within the conceptual modelling framework can be summarized by three theoretical concepts: population heterogeneity, nonstationarity and state dependence. Heterogeneity and nonstationarity may be considered as exogenous determinants of the behavioural process as they determine the decision process environment and include the attributes of individuals or choice alternatives. Heterogeneity constitutes the variation in purchasing (ie. event) probabilities which occur across individuals in a population. Heterogeneity includes the internal characteristics inherent in individuals (described in Section 2.1.1), the socio–environmental influences which are internalized by individuals (such as, culture/subculture, social class, family and reference groups, discussed in Section 2.1.2) as well as individual–specific external influences which do not change over the study period (for example, media habits). Nonstationarity, on the other hand, is the dependence of individual event probabilities on time–varying explanatory variables both those related to the individual and those related to the choice environment.

State dependence is an endogenous factor since it is produced from the behavioural process itself. State dependence may be defined as the dependence of current event probability on past behaviour, future event probabilities on current behaviour, and current event probabilities on anticipated future behaviour, although the latter is seldom considered. Therefore, state dependence considers the influence of a consumer's buying history (of products/brands or store visits) on current or future behaviour as well as the influence of learning, experience (including satisfaction/dissatisfaction) and knowledge on future decision–making behaviour. Four types of state dependence may be identified: (1) Markovian – in which event probabilities depend on the occupation of current state or past states, (2) occurrence – in which event probabilities depend on the number of times different events have occurred in the past, (3) duration – where future event probability depends on the time since the last event took place, and (4) lagged duration – where future event probability depends on the lengths of time between a number of past events. Furthermore, two variations of state dependence are possible: (i) all previous types of states are considered, and (ii) only those lengths of time spent in the same state as the current state are considered (Reader, 1988; Tuma & Hannan, 1984; Wrigley, 1986).

As concepts, heterogeneity, nonstationarity and state dependence should be well defined and distinct although they are often confused in the literature. In a modelling context, this problem of distinction is amplified. For example, duration dependence and heterogeneity could both be invoked as explanations of the so–called 'deficient diagonal' problem of simple Markov models. The deficient diagonal problem describes a situation in which the number of individuals remaining in a state is underpredicted. Some individuals have a greater propensity to move (ie. 'high–risk' movers) and as a consequence, have high transition probabilities. The remainder of the population are low risk movers and therefore have lower mobility probability. However, it can also be argued that the longer an individual remains in a state, the lower the probability that a move will take place and thus transitions are dominated by the length of time spent in any particular state. While both explanations are valid, the question remains as to which determines the transition pattern.

Confusion in the literature over the concepts of heterogeneity, nonstationarity and state dependence, is partly a result of the multidisciplinary nature of consumer research. With one notable exception (Davies & Pickles, 1987), current applied models of consumer shopping behaviour have tended to emphasize the importance of incorporating heterogeneity (Broom & Wrigley, 1983; Jones & Zufryden, 1980; Flinn & Heckman, 1982; Reader, 1988; Wrigley & Dunn, 1985d). Nonstationarity has also received attention, especially in the context of a small number of events occurring per individual (Davies et al., 1982). In contrast, behavioural variation due to state dependence has been relatively neglected. The remainder of this chapter examines alternative modelling approaches which address the spatial and temporal nature of consumer purchasing behaviour.

2.2 Aggregate Modelling Approaches

As a method of analysis, aggregate modelling approaches to consumer behaviour generally assume a high degree of homogeneity between individuals and/or homogeneity of purchasing rates over time. Aggregation of individual behaviour assumes that individuals composing aggregates are basically similar in terms of the decision–making processes which underlie purchase choices (Meyer et al., 1980). In other words, the internal and external factors governing consumer behaviour are assumed to affect all individuals the same way, hence individual heterogeneity is usually ignored. Temporal aggregation occurs when empirical observations are based on a discrete–time sampling scheme which likely differs from the time scale of the behavioural process. Consumer purchasing models have traditionally examined purchasing behaviour at discrete intervals (weeks or months) but empirical evidence indicates that shopping behaviour varies with the time of week and day (Broom & Wrigley; Brunso & Hartgen, 1984; Guy et al., 1983; Uncles, 1985). Models based on a discrete–time sampling scheme examine successive purchasing events as measured in calendar time aggregations and thus the precise timing of intra–interval (ie. intra–week, intra–month) purchases is unknown. For example, if a weekly discrete–time interval is adopted and a consumer is measured as purchasing twice during a particular week, the time during that week when those purchases were made would not be known. Essentially then, aggregate methods typically demonstrate a 'smoothing effect', averaging individuals and generalizing the timing of purchasing events. Consequently, aggregate models tend to emphasize the descriptive aspects of consumer behaviour and while they are often adequate in illustrating the broad patterns of behaviour and their possible determinants they are not capable of isolating the independent effects specific factors have on consumer purchasing behaviour (Shepard & Thomas, 1980).

Aggregate modelling approaches have been used to examine both the spatial and aspatial aspects of consumer behaviour. One way in which spatial choice problems differ from aspatial choice problems is in the number and identifiability of available choice alternatives (Burnett, 1973; Fischer & Nijkamp, 1987; Fotheringham, 1987; Tardiff, 1980). Aspatial alternatives, such as brand choices or transportation modes, are easily identifiable and often few in number, whereas spatial choice alternatives, such as shopping destinations, can be defined in a number of ways, ranging from specific locations (stores) to fairly large spatial aggregates (shopping districts or towns). Furthermore, the number of spatial alternatives available to an individual may be very large, as is often the case in urban areas.

Aggregate models designed to examine spatial purchasing behaviour have largely developed within the geographical literature and concentrate on the analysis of shopping *patterns*. Early studies focused on empirical recognition and explanation of urban retailing within a "Central Place" or "spatial interaction" theoretical framework. Criticism of the practical utility of these early models resulted in some theoretical refinements of the original specifications, resulting in versions with greater applicability to empirical analysis. Spatial models which examine store choice behaviour tend to aggregate individual behaviour, examining the shopping patterns of groups or populations and, also, largely ignore the temporal aspects inherent in consumer purchasing. Alternatively, aspatial aggregate models have tended to address the influence of time in consumer behaviour through 'purchase incidence' models, which aim to predict when a purchase will occur.

Developed in the marketing research literature, 'purchase incidence' models have proven useful in identifying general patterns of behaviour and have been found to closely approximate empirically observed purchasing patterns (Chatfield et al., 1966; Ehrenberg, 1988; 1968; 1959; Frisbie, 1980; Goodhardt et al., 1984). More recent aspatial studies are concerned with generalizing these 'purchase incidence' models, by disaggregating them and making the model parameters dependent on explanatory variables (ie. population heterogeneity) (Broom & Wrigley, 1983; Jones & Zufryden, 1980; Wrigley & Dunn, 1985d). However, any analysis of the effects of different sampling schemes of temporal aggregation in purchase incidence models has been relatively neglected (Davies & Pickles, 1987; Ehrenberg, 1968; Goodhardt et al, 1984; Wrigley & Dunn, 1984a).

Attempts to merge the spatial and aspatial components of consumer purchasing behaviour has resulted in the development of store choice frequency models which link a (spatial) store choice component with a (aspatial) purchase incidence component (Broom & Wrigley, 1983; Kau & Ehrenberg, 1988; Wrigley & Dunn, 1984a; 1984b). Davies and Pickles (1987) propose a joint–trip timing, store–type choice model which simultaneously considers both continuous–time and discrete–choice shopping behaviour. The remainder of this section discusses the developments in spatial and aspatial aggregate modelling approaches with emphasis on the attempts made to generalize these models.

2.2.1 Central Place Theory

Central Place theory (CPT), as developed by Christaller in the 1930s, provides a conceptual model for the spatial analysis and description of the optimum size, number, distribution and function of service centres (ie. retail and service businesses). Within the CPT framework, systems of retail centres are assumed to be in a constant state of adjustment with the distribution of consumer demand across a city or, between cities. CPT aims to explain an apparent order among patterns of central places which dispense goods and services to a surrounding area. The theory proposes that knowledge of the exact demand for goods and services generated by an area is the only information needed to predict the spatial pattern of retail activities, and is based upon a notion of 'least–effort' for consumer behaviour

(Jones & Simmons, 1987). This relationship between consumer demand and retail activity patterns is based on a number of assumptions which construct a simplified view of the distribution system.

CPT assumes that a fixed number of store types serve an entire area and that retailers, having complete knowledge, make optimal location decisions. The retailers decision is assumed to be determined by the *threshold* value, below which a good cannot economically be offered for sale. In other words, a minimum population is required to support a good and the size of this population defines the *threshold* of the good, which in turn, dictates the size of the trade area. Different goods are reasoned to have different trade areas thus centres offering goods can be classified into a hierarchy in which high–ranking centres offer both high–order goods and the goods and services offered by lower–ranking centres. Hexagonal trade areas are assumed to form due to the free entry of business, so restricting trade areas to their minimum size (Beavon, 1977). Consequently, the location patterns of central places emerges as an ordered, nested retail hierarchy of hexagonal trade areas. Furthermore, the CPT retail pattern can exist between areas, ranging from low–order hamlets to high–order urban areas, as well as within areas, from low–order street corner service stations to high–order regional art galleries (Beavon, 1977; Johnston & Wrigley, 1981; Kivell & Shaw, 1980; Jones & Simmons, 1987; Thorpe & Nader, 1967).

CPT has been used extensively by geographers for a variety of purposes including empirical testing of the model's hierarchical centres in urban retail structures and assessing the validity of the behavioural tenents of the theory (for example, see Beavon, 1977; Bucklin, 1971; Curry, 1967; Thorpe & Nader, 1967). Several comprehensive reviews of the derivation and content of CPT exist elsewhere (for example, see Beavon, 1977) and this thesis limits itself to a discussion of the validity of the main theoretical arguments.

One of the fundamental requirements of CPT is that consumers are assumed to have equal purchasing power and are spread evenly over an isotropic plane in such a way that distance is the only factor impeding individual travel. Beavon (1977) debates whether Christaller explicitly specified this assumption or whether it is the result of a misinterpretation of his work, saying: "...Christaller does not, and need not, assume an isotropic plane for the development of his central place systems" and a "...regular but not necessarily even distribution of population" is required (Beavon, 1977:40). The specificity of this assumption may be questionable but the implication is that a type of homogeneous transportation surface is required by the model so that consumers attempt to minimize their travel costs by visiting the nearest store offering the single required good (or service). Empirical studies demonstrate that a tendency exists for consumers to select nearby stores but many individuals do not patronize the store closest to their residence (Davies & Pickles, 1987; Fotheringham, 1988; Gautchi, 1981; Kau & Ehrenberg, 1988; Lamb & Goodhardt, 1988; O'Kelly, 1981; Wrigley & Dunn, 1985d), and this *nearest centre* tendency differs for different product types. For example, Thorpe & Nader (1967) found that of the consumers who tended to visit the nearest store, visits to the closest store for food products occurred more frequently than nearest centre visits for non–food items. Furthermore, consumers often tend to minimize their total travel effort by combining shop visits in a multipurpose trip, rather than minimize the travel cost for a single good (Ghosh & McLafferty, 1984; Hanson, 1980; Kitamura, 1983; Kostyniuk & Kitamura, 1984; Mulligan, 1983; O'Kelly, 1981) and may visit more distant centres than the nearest centre if price savings for the required goods exceed the additional transportation costs. Therefore, it appears that the *nearest centre* hypothesis is a serious overstatement of behavioural realities and at best, can only be considered as a partial explanation for consumer shopping behaviour.

Another behavioural assumption inherent in CPT is that consumers have perfect information, allowing them to make economically rational decisions and thus minimize the time–cost budget of their shopping journey. In reality, consumer shopping behaviour is constrained by the fact that individuals will likely have incomplete knowledge of the overall nature of the supply system and will, for various reasons, be satisfied with taking a trip that does not necessarily result in the economic optimum of the potential opportunities. Also, the range of possible shopping alternatives constantly varies (Shepard & Thomas, 1980), partly attributable to changes in personal mobility and perception. Thus CPT, which constrains shopping behaviour to a stationary, least–effort, one–centre scenario (Kivell & Shaw, 1980), fails to represent the modern reality of consumer mobility and information. For example, Bucklin (1971) found that spatial competition is an important influence on consumer trip–making behaviour and consumers were more prone to cross trade area boundaries for shorter shopping trips than for longer journeys. Rejection of the nearest centre hypothesis and the rigid geometry of CPT trade areas does not imply that no order exists in spatial behaviour (Beavon, 1977), but it appears as though actual behaviour does not conform to the models theoretical requirements.

Using knowledge of the distribution of consumer demand and the spatial structure of a shopping system, CPT can provide a simple model for predicting the vast majority of spatial interaction and retail planning decisions. However, in reality, there are a number of influences which complicate the theoretical pattern provided by CPT since retail centres vary in accordance with differences in local consumer demand, caused by demographic, ethnic or social conditions and their locations are determined by intra–urban accessibility, population distributions and income and planning regulations. The strength of the CPT relationship between structure and behaviour appears to be assumed rather than demonstrated (Curry, 1967; Kivell & Shaw, 1980; Shepard & Thomas, 1980) and inclusion of empirically observed behaviour in a CPT framework would likely modify the theory out of recognition. Essentially, the value of CPT is that it is an abstract, simplified view of the distribution system, providing a 'theoretical norm' with which comparison can be made to assess the extent to which the basic theoretical assumptions hold. CPT has been extremely influential in the development of retail shopping analysis, generating a prodigious amount of work regarding the spatial structure of shopping opportunities, but, due to its limitations, progress in really understanding consumer behaviour will most likely occur through an alternate framework.

2.2.2 Spatial Interaction Theory

Spatial Interaction theory provides an alternative model to CPT and is designed to describe, explain and forecast any type of movement resulting from human processes. With such a general definition, spatial interaction models (SIMs) can be used to examine a wide range of phenomena such as shopping, migration, commodity flows, commuting, public and private facility utilization patterns and the transmission of knowledge and information. SIMs have been a fundamental technique in location analysis, used extensively by city planners, transportation analysts, land developers. In retailing, SIMs are used for a variety of purposes, including estimation of trade areas, locating new stores, assessing the impacts of store openings and closings on retail networks and forecasting consumer movements (Ducca & Wilson, 1976; Haynes & Fotheringham, 1984; Johnston & Wrigley, 1981; Jones & Simmons, 1987; Kivell & Shaw, 1980; Shepard & Thomas, 1980; Wilson, 1988). However, SIMs have generally been limited to assumed static equilibrium conditions and only apply to an urban system for a point in time, neglecting the dynamics of urban markets and micro–variations in consumer behaviour.

Within the spatial interaction framework, the CPT assumption that consumer behaviour is explained by a nearest centre hypothesis is discarded and, instead, shopping patterns are assumed to be determined by a more complex tradeoff between the advantages of centre size (scale) and the disadvantages of distance. Scale and distance are the two primary components of SIMs and their relationship is based on Reilly's 'law of retail gravitation', a notion intuitively analogous to Newtonian physics and reinforced by empirical observation of shopping behaviour at the inter–urban scale (Haynes & Fotheringham, 1984; Shepard & Thomas, 1980). Simply put, the so–called gravity model postulates that a centre attracts retail trade from its surrounding region in direct proportion to the centres size (ie. population) and in inverse proportion to the square of the distance from the centre. Competition effects are assumed to distribute consumers between centres by allocating flows from the intermediate area, resulting in 'breaking points', where the attraction powers of two competing centres are evenly balanced. The breaking point distance divides market flows equally, defining market area boundaries, and the consumers located on these boundaries are assumed to be indifferent to the market centre they patronize. However, trade areas are not permanently fixed in space or time and while breaking points may be useful indicators of general market patterns interaction often takes place across trade area boundaries (Bucklin, 1971; Foot, 1981; Haynes & Fotheringham, 1984; Kivell & Shaw, 1980). Furthermore, the conventional adoption of a distance parameter equal to 2.0 has no inherent behavioural justification, and it is likely that such distance effects vary by region, mode of transportation, type of retailing, competition from other stores, consumer income, shopping frequency, etc. For example, larger parameters are typically associated with purchases of convenience goods, whilst smaller parameters tend to be associated with the purchase of consumer durables (Bucklin, 1971; Haynes & Fotheringham, 1984).

Reilly's gravity model provides deterministic solutions for general patterns of aggregate consumer flows and, since its original construction, the gravity model has evolved to a more general model which can be used to examine both aggregate and disaggregate probabilistic purchasing patterns. Huff (1963) recognized the limitations of Reilly's original model and reformulated it to examine the interaction between centres in an urban system. Instead of focusing on interaction between a single pair of centres, Huff generalized the model to distinguish between origin and destination locations and to calculate movement to a particular centre as a probability function of all potential destinations within the system. Huff also redefined the attractiveness of a centre to be a function of retail floor space, not simply population, and treats the constraint of distance as a function of travel time, rather than simply straight line distance. Huff's (1963) version of the gravity model was later expanded by Lakshmanan & Hansen (1965) to include an empirically derived parameter for the relative influence centre size may have in attracting consumers. An 'attractiveness' parameter is introduced to account for the fact that a larger centre is likely to be disproportionately more attractive than a smaller centre, due to the potential for comparison shopping or multi–purpose trips. In practical applications, the attractiveness of a centre as a function of the number of stores, floor area, sales, or the number of different types of stores (Beavon, 1977; Haynes & Fotheringham, 1984; Jones & Simmons, 1987).

Gravity models treat the probability that a consumer will visit a particular store as an inverse function of competing facilities, so allowing overlap between trade areas and permitting consumer flows across market boundaries. Competition is an important influence on the choice of a shopping destination and a further modification to the gravity model is the **competing destinations** model, which includes a variable to express the agglomeration effects on flow interactions which result from the relative locations of centres. The **intervening opportunities** model, developed by Stouffer in the 1940s, provides an alternative model to examine competition effects. The intervening opportunities model is a variant of the gravity model which redefines the cost of a trip as a function of the number of intervening potential destinations which offer the required good/service that lie between the consumer's origin and a possible destination. While the theoretical basis of the intervening opportunities model appears to be less plausible than that of the gravity models (Wilson, 1967), it is apparent that Reilly's implied theory of distance as an invariant exponent which acts as a universal deterrent for a given shopping trip is unlikely, and a more appropriate representation of trip behaviour would include some type of evaluation of the relative importance competing destinations have for a particular journey. For example, Bucklin (1971) found that the overlap between competing trade areas is an important influence on trip behaviour and the magnitude of this influence varies with different product types. From consumer surveys on intra–urban shopping patterns he consistently found that as the distance between pairs of competing centres increases, the extent of overlap (and hence the propensity to visit alternative stores) is enhanced for purchases of automobiles, household durables and grocery products.

Various types of gravity models have also been generated from Lakshmanan & Hansen's (1965) original formula, resulting in a family of gravity models which are based on constraints that may arise in a particular application. The **total flow constrained gravity** model considers estimation of the interaction pattern of a system when only the total amount of flows are known. The **production–constrained gravity** model estimates the total flows in a system based on knowledge of the total number of outflows for each origin in the system while the **attraction–constrained gravity** models predict total flows from data on the total number of inflows to destinations. Lastly, the **doubly–constrained gravity** model forecasts the total flow pattern within a system based on information of the total outflows from each origin and in total inflows to each destination. Comparison of the four gravity models indicates that the more constraints placed on the model the greater the accuracy of predicted interactions (see Haynes & Fotheringham, 1984 for details). This is not surprising because singly–constrained models are essentially demand models with activities reallocated to zones (either origin or destination) without any reference to the level of supply in these zones. However, when both supply and demand are considered (ie. doubly–constrained models) better representation of the actual urban system occurs.

The practical modifications to Reilly's model increase the gravity models flexibility, enabling comparison of consumer flows for different types of trips (such as singly or doubly constrained trips or durable versus non–durable trips) and studies of individual shopping behaviour (by including socio–economic characteristics of consumers). These disaggregated gravity models require empirically determined parameter values for the 'attractiveness' and 'disincentive' terms and the survey cost associated with deriving this empirical data is considerable. Consequently, previous values for these parameters are often assumed transferable from similar studies. However, this can lead to values which are not empirically derived for a particular application and may result in the problem that, while the model appears to be mechanically sound, it may bear little relation to the behavioural interaction which it is assumed to be modelling (Shepard & Thomas, 1980). Furthermore, using calibrated parameter values for the distance or attractiveness variables in model forecasting assumes that the behavioural trip pattern established at calibration also holds at prediction (see Ducca & Wilson, 1976 for an example of such a method). However, this rationale will likely result in insufficient forecasts of changes in urban systems because any effects a new facility may have on existing structures will most certainly affect existing behavioural patterns, and at best, such a method can provide only minimal estimates. In fact, a major criticism of the gravity model is that it is only a 'partial' model, simulating interaction for one activity while holding all other parts of the urban system constant (Foot, 1981; Kivell & Shaw, 1980). In reality, all parts of the urban system interact simultaneously and the dynamic elements within the system result in continual modification of behaviour patterns. Attempts to develop more realistic models, by introducing dynamic elements into SIMs have been made (for example, Wilson, 1988) but the conceptual formulation of such models is extremely complex and the data requirements are enormous. Therefore, SIMs typically provide statistical description for existing urban systems but are generally insufficient for predictive purposes since they are largely divorced from the behavioural process which they aim to relate. SIMs may be useful in predicting the allocation of shopping facilities where there is short–term incremental growth of population or changes in the urban system, but the longer the time span the more misleading the results (Kivell & Shaw, 1980; Shepard & Thomas, 1980). Perhaps, as Gautschi (1981) suggests, a potentially more fruitful area for spatial behaviour investigation lies in examining consumer choice domains in terms of shopping trips rather than shopping destinations.

2.2.3 Trip–Chaining Analysis

Traditional spatial choice theory, provided by Central Place theory and Spatial Interaction theory, quickly becomes very complex when dealing with 'multipurpose' trips, where in this context, 'multipurpose' refers to trips that include visits to several centres. The importance of 'multipurpose' trips, where 'multipurpose' takes on a slightly broader definition to also include several orders of goods, has been illustrated by empirical evidence which indicates 30 to 50 percent of all shopping trips are so defined (Hanson, 1980; O'Kelly, 1981). Closely related to multipurpose trips is the concept of 'combined purpose' trips which reflect journeys that combine a number of activities into a single trip, such as work with shopping, recreation with shopping, or personal business with shopping. Thus, it is unlikely that traditional spatial choice models can reveal accurate representation of consumer spatial behaviour since they bear little resemblance to actual decision–making patterns nor are they likely to provide explanation as to *why* observed patterns of spatial behaviour occur or *how* they develop (Hanson, 1980). Recognition of this fact led to the development of trip–chaining analysis which specifically examines the existence and complexity of observed trip–making behaviour.

Originating in the economic and transportation literature, trip–chaining studies gained popularity in the 1960s (Thill & Thomas, 1987) and have since been used to explicitly examine the ways individuals organize and manage activities, with the goal of providing insight into the underlying behaviour such trip patterns reflect. Different aspects of travel patterns have been examined in trip chaining studies, including the sequencing of trips (Kitamura, 1984; 1983; Kitamura & Kermanshah, 1983; Lerman, 1979), the locational aspects of multiple trip destinations (Ghosh & McLafferty, 1984; Mulligan, 1983; O'Kelly, 1981), the type of trip linkages (Anderson, 1971; Chapin & Brail, 1969; Clarke et al., 1981; Hanson, 1980; Kitamura, 1985; Kitamura & Kermanshah, 1984; Kitamura et al., 1981; Kondo & Kitamura, 1987; O'Kelly, 1981), and the temporal stability of trip chains (Kostyniuk & Kitamura, 1984). However, progress in trip–chaining research has been hampered by a lack of homogeneity in the definition and measure of trip–chaining travel patterns (Shepard & Thomas, 1980; Thill & Thomas, 1987).

For the purposes of this discussion, trip–chaining refers to multistage travel patterns, which include both multipurpose and multi–stop trips. Trip–chaining records are frequently based on travel diaries kept by individuals for specific lengths of time (Clarke et al., 1982; Hanson, 1980; Kostyniuk & Kitamura, 1984; O'Kelly, 1981), but consistent and reliable results are often not achieved regarding the compositional factors of trip chains due to the diversity of study designs which have been used. For example, within urban spatial research, trip–chain records are envisioned as a practical means of gauging the general quality of urban life and the overall efficiency of urban systems, where such records are viewed as outcomes which either reflect individual choices or can be used as a means of evaluating the constraints imposed by urban environments on the daily patterns of life (Anderson, 1971).

Research indicates that of all the major activities undertaken by urban residents, shopping tends to interact most strongly with other activities (O'Kelly, 1981; Shepard & Thomas, 1980). Several variables could be used to determine the relative importance of shopping and non–shopping trip components such as duration, money spent, motives, priorities and degree of pre–planning. Time, however, is a quantitative measure which is highly appropriate to social organization studies because it can serve as a scale upon which most, if not all, activities and interrelationships can (in principle) be measured (see Anderson, 1971). As a result, time is commonly used as a unifying variable across which an individual organizes a range of activities, that is, creates trip chains (Shepard & Thomas, 1980). Methods of managing time to create trip chains is often treated as a 'time–budgeting' problem, wherein the time available governs the allocation, type, duration and sequencing of activities. A large body of time–budget literature has grown from this central idea and includes work which extends the time–budget premise to a spatial dimension thus making budget–type analysis more relevant to geographers and planners (see reviews by Anderson, 1971; Thill & Thomas, 1987). A time–budget describes an individuals use of time, typically over a short period, and contains information on the sequence, timing and duration of activities. In addition to time–budget information, space–time budgets include the spatial coordinates of activity locations.

The interrelationships between the uses of space and time for activities has been comprehensively studied by Hägerstrand and his colleagues (Anderson, 1971). Hägerstrand identifies three sets of constraints on space and time resources: (1) *capability constraints*, which involve physiological regulators (such as age and sleep) as well as physical mobility; (2) *coupling constraints*, which operate within the first set of constraints and are based on the need for individuals, tools and materials for timing and synchronizing activities in space; and (3) *authority constraints*, which refer to limitations and control of access imposed by society (Anderson, 1971; Shepard & Thomas, 1980). In this so–called 'constraints' approach individual choices are decided within the limits of social, spatial and temporal constraints and thus shopping is related to all other activities in a unified fashion. In fact, Shepard and Thomas (1980) note that shopping is particularly subject to the second set of constraints, that is, those imposed by an individuals participation in other activities. Therefore, the root concept of the budget approach to trip chaining is that decision–making is not a free process but strict interdependence exists between various activities over time.

A major criticism of Hägerstrand's 'constraints' approach is that emphasis on the constraints of behaviour and the consequent downplaying of individual choice can lead to a misrepresentation of observed behaviour. The conceptual distinction between choice–based and constraint–based behaviour forms the basis of two distinct approaches to studies of human behaviour in time and space, ie. the active decision–making approach and the reactive decision–making approach (Thrift, 1981). In the former, individuals are considered as actively processing available information and choosing between alternatives based on their perceptions. The latter tradition, on the other hand, views individual decisions as the outcome of constraints which limit the available choices and govern decisions. Hägerstrand's work adopts the reactive approach, emphasizing the limits within which choices are made.

Within the active decision–making tradition trip studies have been based on the principle of utility maximization (discussed in detail in Section 2.3). Briefly, in trip–chaining analysis, utility maximization assumes that individuals minimize the 'negative' determinants of behaviour (for example, time or cost) by combining activities into an 'optimal' sequence. Theoretical trip chaining applications of utility maximization have developed mainly within CPT studies and are typically concerned with purchases of commodities and services to the exclusion of other travel purposes (Thill & Thomas, 1987). In general, these theoretical studies focus on limited aspects of trip–chaining behaviour (Bacon, 1984; Ghosh & McLafferty, 1984; Kitamura, 1984) or examine supply–side properties which are linked to the formation of trip chains (Bacon, 1984; Mulligan, 1983). This approach has been valuable toward formal conceptualization of trip–chaining behaviour but Thill and Thomas (1987) conclude this framework does not successfully deal with the spatiality of trip chaining or central place structures.

Alternative approaches to trip–chaining analysis include simple statistical techniques, such as factor analysis (Chapin & Brail, 1969) to investigate the influence of individual characteristics or spatial factors (for example, transportation access) on travel behaviour. Multivariate models have also been used to clarify the relations between socio–demographic variables and constraints on travel patterns (Kostyniuk & Kitamura, 1984), and for testing the temporal stability of travel patterns (Kostyniuk & Kitamura, 1984). The results of these studies indicate that actual trip choice decisions are more complex than proposed by traditional spatial choice theory, however, trip–chaining investigations typically analyze different aspects of trip–chaining behaviour (ie. the sequencing, location and type of stops) independently from one another. Such methods therefore, fail to grasp the fundamental mechanisms of trip–chaining because the simple statistical framework is inadequate for examining temporal aspects of travel behaviour and the factors influencing trip decisions in a unified fashion.

Theoretical approaches to trip–chaining analysis focus on overt spatial behaviour and individual perceptions of the physical environment and may provide comprehensive description of activity patterns which are not directly observable due to their spatial and temporal extent. Trip–chaining studies tend to examine individual travel behaviour but aggregation occurs when a large number of activity patterns are categorized under a single label (Chapin & Brail, 1969). Moreover, what constitutes a shopping trip as opposed to a social or entertainment trip on which a good was purchased will depend on the definitions of such categories of activities. Space/time–budgeting approaches address the notion that tradeoffs exist between time allocation and space–time preferences and while this may be conceptually appealing it is unlikely that such methods will provide independent behavioural postulates from which improved theories of spatial behaviour can be derived. As Anderson (1971) notes, constraints are implicit in choice decisions, the relative emphasis given to the 'positive' and 'negative' determinants of behaviour leads to crude distinctions between what constitutes a choice and what constitutes a constraint in a particular situation. In reality, individuals base their decisions on both choice and constraints and these opposing views form a continuum rather than a dichotomy (Thrift, 1981).

2.2.4 Purchase Incidence Models

Purchase incidence models of consumer behaviour are concerned with predicting when a choice decision will be made, ie. when a shopping trip is generated. The goal of purchase incidence models is to identify behaviour patterns from 'random' variation due to other effects. Massy et al. (1970) provide a detailed review of purchase incidence models which have developed within the marketing research literature since the 1950's. The authors distinguish between two general classes of purchase incidence models, those which focus on purchase incidence for a total product class and those which emphasize purchase incidence for a particular alternative, ie. a brand or store. Purchases are discrete events that occur at specific points in time and thus, purchase incidence models are aimed at determining the probability distribution of observations during a specified interval of time. Models therefore, take the form of a stochastic process in which the probability of observing exactly one purchase is equivalent to the joint probability of all purchase events. Purchase incidence models may be used to predict the probability distribution of total demand for new or established products or for studies of brand choice (see Massy et al., 1970 for details). Essentially, product demand and brand choice are examined by predicting the total number of purchases of each type of product/brand during fixed, aggregate, time intervals (for a homogeneous product class), but this method is likely to be more appropriate for established products rather than for new products (Massy et al., 1970) because it assumes that the process generating purchases is fairly stable over time, something which is more likely to occur once a product/brand has been on the market for some time.

Purchase incidence models are formulated upon an assumed distribution for the 'time between events'. For example, exponentially distributed 'times between events' would follow from a Poisson purchasing process. Purchase incidence may also include provision for response uncertainty and is generally achieved by assuming that certain relevant parameters of the instantaneous purchasing rate are distributed among members of the population according to a specified distribution function. Hence distributional assumptions are used to parameterize both the actual purchase incidence component and any response uncertainty. For instance, a negative binomial distribution (NBD model) for the number of purchases in a specified time period results when a Poisson process is assumed for the purchase incidence component and a gamma distribution is assumed for the response uncertainty component. The NBD is perhaps the most popular purchase incidence model and has been applied extensively in commercial studies of brand purchasing for over twenty years (see Ehrenberg, 1972). Early applications of the NBD model were concerned with forecasting purchase frequency into future time periods and to quantitatively assess NBD predictions against empirically observed purchasing patterns. The NBD model generally provides reasonable estimates of observed purchasing behaviour for frequently bought non–durables (Chatfield & Goodhardt, 1975; Chatfield et al., 1966; Dunn et al., 1983; Ehrenberg, 1959; 1968; Kau & Ehrenberg, 1984; Wrigley & Dunn, 1984a; Wrigley, 1980) and for store trips which involve relatively small expenditures (Frisbie, 1980).

The NBD model is based on three behavioural assumptions. These are that (1) the average number of purchases of a particular alternative is constant over successive time periods; (2) the number of purchases made by an individual follow a Poisson distribution in successive, equal time periods; and (3) long–term average purchasing rates by different consumers follows a two–parameter gamma distribution. The NBD is, therefore, a two–dimensional model with one dimension in time and the other concerning the characteristics of the individual consumer (Timmermans & Borgers, 1989). The Poisson assumption for purchase incidence means that purchases in successive time periods are independent. This means that the NBD model ignores time dependence in the purchasing process (Section 1.6),ie. the purchasing rate is assumed constant, and hence interpurchase times (ie. durations) are exponentially distributed. This exponential distribution, coupled with the gamma assumption for population heterogeneity results in a negative binomial distribution for the number of purchases of a particular brand (at a particular store) by consumers in a given observation period.

The three behavioural assumptions of the NBD model essentially result in theoretical 'norms' of purchasing behaviour against which empirically observed buying patterns can be compared. As with the CPT models of Section 2.2.1, discrepancy between NBD theoretical 'norms' and observed behaviour can represent deviations from 'no trend', ie. stationarity, conditions. This type of comparative analysis may provide insight into observed purchasing behaviour (see for example, Ehrenberg, 1959; Wrigley & Dunn, 1988), but a common limitation of these studies is that they involve (by default) some degree of data aggregation by having either purchasing periods of no less than one week (ie. temporally aggregated data) (Ehrenberg, 1959) or by categorizing individual stores into store types or groups (ie. spatially aggregated data) (Wrigley & Dunn, 1988). Furthermore, consistent discrepancies between NBD estimates and observed behaviour appear to occur in extreme buying situations, for example, when the sample data is skewed by a large number of 'heavy' buyers purchasing at suburban stores (Dunn et al., 1983; Ehrenberg, 1968; 1988; Frisbie, 1980; Wrigley & Dunn, 1984a). This consistent discrepancy is often called 'variance discrepancy' or a 'shelving effect' (Chatfield et al., 1966; Ehrenberg, 1959) and results from a breakdown of the gamma assumption in representing the purchasing rates of different consumers, systematically overestimating the proportion of heavy buyers. Variance discrepancy also occurs when buying trips are spatially defined because relatively remote stores (such as suburban stores) tend to have smaller catchment area populations due to the differential accessibility of consumers (Dunn et al., 1983; Massy et al., 1970; Wrigley & Dunn, 1984a; 1984b; 1984c; 1985d; 1988). NBD predictions are improved when probability estimates are based on the 'relevant population' which is obtained by calibrating the model on a sub–sample of the purchasing population who are 'heavy' buyers or who reside in the local trade areas of the stores (Wrigley & Dunn, 1988).

Variance discrepancy observed in NBD model applications is less apparent when a **Beta–Binomial Distribution** (BBD) is applied to the same data (see Chatfield & Goodhardt, 1975; 1970). The BBD model examines the number of weeks in which a consumer makes at least one purchase of a particular brand (or equivalently buys at least once at a particular store). The two behavioural assumptions of the BBD model are that firstly, a given consumer buys at least one unit of/at a brand/store in a particular week at a constant probability, p, which is independent of previous purchases (ie. the NBD Poisson assumption). Moreover, in n weeks a consumers purchasing rate follows a binomial distribution with parameters n and p. The second assumption is that this probability, p, varies across the consuming population as a beta distribution. The two basic differences between the BBD and NBD behavioural assumptions are that the BBD assumes a beta distribution for population heterogeneity whereas the NBD assumes a gamma distribution, and BBD estimates focus on the number of purchasing weeks whereas NBD estimates examine the number of purchases in a specified interval of time. The BBD concept of a 'purchasing week' however, has dubious application in marketing research because of the lack of standardization in data collection techniques and the fact that different products can have different purchasing rates which may not conform to a weekly time–scale. These differences in purchasing rates for different products is summarized by the term 'inventory effects'. 'Inventory effects' represent the length of time (ie. duration) between repeated product purchases. For example, bread has a higher re–purchase rate than laundry soap and this difference would be expressed in the inventory effects of the different products.

The NBD and BBD models both examine purchases of a single brand or equivalently, shop visits to a single store. However, as indicated earlier (see Section 2.2.3), observed shopping patterns often exhibit multi–store purchasing behaviour. Alternatively, the NBD–Dirichlet (or more simply, **Dirichlet**) describes multi–brand/multi–store purchasing behaviour in a stationary unsegmented market (Chatfield & Goodhardt, 1975; Ehrenberg, 1988; Goodhardt et al., 1984). The Dirichlet model specifies probabilistically how many purchases/visits each consumer makes in a specified time period and which brand/store is chosen on each occasion. The Dirichlet's behavioural assumptions are that (1) brand/store choices are independent with a constant average purchasing rate, implying that the number of purchases in each equal length time period follows a Poisson distribution; (2) purchasing rates of different consumers, ie. population heterogeneity, follows a gamma distribution; (3) individual choice probabilities are constant over time and independent over successive purchases, implying that the number of purchases of each alternative made by an individual in a purchasing sequence follows a multinomial distribution; (4) choice probabilities follow a multivariate–beta or 'Dirichlet' distribution across consumers; and (5) store choice probabilities and average purchasing frequencies of different individuals are independently distributed over the population. The Dirichlet is a two stage model, the first stage dealing with the distribution of purchases (assumptions (2) and (3)), and the second stage allocating the number of purchases between alternative brands/stores (assumptions (1) and (4)). The fifth assumption implies that the distribution of brand/store choice probabilities is the same for light, medium and heavy buyers (Timmermans & Borgers, 1989).

Therefore, the Dirichlet model is a brand/store choice frequency model, linking an aspatial purchase incidence component with an aspatial brand choice or a spatial store choice component. In the Dirichlet model, purchase incidence and brand/store choice are jointly determined which requires certain input parameters, two of which, namely individual purchasing rates and individual choice preferences, correspond to population heterogeneity (Ehrenberg, 1988; Goodhardt et al., 1984). If only two brand/store choices are considered, ie. a binary choice situation, the

Dirichlet model reduces to the BBD model and from assumptions (1) and (2) it follows that the number of purchases made by all individuals in a specified time period follows a NBD.

The Dirichlet model is a flexible, testable model which has proven to have a wide range of applicability. In addition to making prediction associated with the NBD and BBD models, the Dirichlet has been used to assess the linkages between individual brands/stores (Wrigley & Dunn, 1984b; O'Kelly, 1981); the degree of brand/store loyalty (Ehrenberg, 1988; Goodhardt et al., 1984; Uncles, 1988); for predicting brand purchases within store groups (Kau & Ehrenberg, 1984); and for multi–brand purchasing patterns within individual stores (Wrigley & Dunn, 1984b; 1984c; 1988). For example, Wrigley and Dunn (1984b) apply the Dirichlet model to intra–urban multistore purchase patterns and in a subsequent publication (1984c) they investigate the models applicability to multibrand purchasing by individuals/households and within individual stores. Their results indicate the model's sensitivity to extreme buying situations and, when the model is recalibrated to examine local store trade areas or individual stores, theoretical estimates improve (see Wrigley & Dunn, 1984c for details). The results of these applications therefore reinforce the importance of calibrating consumer purchasing models to the 'relevant population' in order to minimize the variance discrepancy.

The NBD, BBD and Dirichlet models all assume both short–term and long–term stationarity conditions (Section 1.6), partly reflecting the level of temporal aggregation commonly used in purchasing behaviour studies which examine buying patterns over weeks and multiples of weeks and thus neglect short–term (intra–week) nonstationarity conditions (Chatfield et al., 1966; Ehrenberg, 1988). In short–term stationarity conditions it is assumed that purchasing rates remain the same from one time period to the next and time periods are equal when in reality, individual purchasing rates vary from one period to the next (Broom & Wrigley, 1983; Guy et al., 1983; Uncles, 1985). Long–term stationarity conditions are a more reasonable assumption in a relatively short–run behavioural process, such as shopping, than in other behaviour process studies, such as, for example, labour force dynamics (Flinn & Heckman, 1982; Reader, 1988). Schmittlein et al. (1985) extended the BBD model to examine purchase incidence in nonstationarity environments by formulating non–linear conditional expectations of the number of purchases made by a consumer. Their results indicate that it may be possible to identify the influence of different purchasing rates on changes in overall sales, but it appears that the apparent success of the NBD model is partly attributable to the fact that linearity in conditional expectations typically occur in empirical samples (see Schmittlein et al., 1985 for details).

Given this lack of consideration for nonstationarity conditions, generalizations of purchase incidence models have tended to focus on incorporating behavioural variation due to population heterogeneity. Several authors have proposed models which basically add a vector of explanatory variables to the purchase incidence, 'distributional–based' models (Broom & Wrigley, 1983; Massy et al., 1970; Wrigley and Dunn, 1985d). An alternative method of incorporating heterogeneity, developed and empirically examined by Jones and Zufryden (1980; 1982), examines nested choice decisions by integrating a logit model for the brand choice probability with a Poisson purchase incidence model that includes a vector of explanatory variables. Although vectors of explanatory variables can identify sources of individual variation, model estimates are largely governed by the particular mixing distribution chosen to represent population heterogeneity (Heckman & Singer, 1986). Furthermore, Allison (1984) argues that it is unrealistic to assume that *all* sources of heterogeneity can be measured and included in a vector of explanatory variables. In fact, some authors believe that it is the unobservable variables, including those which are potentially measurable and those generally unmeasurable, which are crucial to understanding consumer behaviour variation due to heterogeneity (Dunn & Wrigley, 1985; Flinn & Heckman, 1982; Hannan, 1984; Heckman & Singer, 1986; Reader, 1988; Wrigley, 1986). Wrigley (1986) provides a particularly good discussion of the effects of unobserved heterogeneity on both behavioural implications and model parameters. One method which would, in principle, allow unobserved heterogeneity to be separated from other sources of behavioural variation would be to expand the existing model to include a disturbance term (Heckman, 1981a).

The Poisson assumption inherent in purchase incidence models implies that purchasing behaviour is a random process and while this may be an appropriate assumption for some consumers, 'heavy' buyers appear to have significantly more regular inter–purchase times than expected under the Poisson assumption (Dunn et al., 1983; Wrigley & Dunn, 1988). N–order Erlang processes (where $n \geq 2$) allow the modelling of 'more regular than random' purchasing and present reasonable computational alternatives to the Poisson distribution (Jeuland et al., 1980). These Erlang processes allow for the intuitively pleasing notion of purchasing probability being allowed to be at a minimum immediately after a purchase has been made. Zufryden (1977) examined the use of a second–order Erlang distribution for purchase incidence whilst allowing the purchase probability to vary over the population according to a beta distribution and his empirical results indicate that the model appears to perform extremely well (Zufryden, 1978). Chatfield and Goodhardt (1973) analyzed the benefits associated with Erlang processes of different orders and their results indicate that whilst the second–order Erlang distribution more adequately represented 'heavy' buyer purchasing rates, the small improvement in model fit is at the expense of a substantial increase in model complexity. Alternatively, an inverse gaussian distribution has been proposed to account for interpurchase times (see Banerjee & Bhattacharyya, 1976) and appears to be more robust than the NBD for small purchasing rates (those of one to two weeks), but again, the small improvement of model accuracy is of little value compared to the increase in model complexity (Borgers & Timmermans, 1987; Broom & Wrigley, 1983).

Davies and Pickles (1987) provide the most advanced application to date of a generalized dynamic consumer choice frequency model. Their joint–trip timing, store–type choice frequency model considers the actual sequence of trip timing and the destination choices and their model addresses continous–time, discrete–state shopping behaviour. The steady state depletion of grocery items is specified by an inverse gaussian distribution which, in turn, identifies a shopping event whenever a consumption threshold is crossed, thereby incorporating inventory effects into the model (Section 2.4). Davies and Pickles (1987) include a vector of explanatory variables to account for observed population heterogeneity and they allow for nonparametric control for the omitted/unobserved components of heterogeneity. At the temporal level considered by Davies and Pickles (1987), both nonstationarity and state dependence are identified as being influential in observed shopping behaviour. In particular, their results provide clear support for relaxing the independence (ie. Poisson) assumption for store choice showing that it is inappropriate since households exhibit a degree of ordering between supermarket and local trips. Davies and Pickles' (1987) conclude that the theoretical notion of inventory effects is well grounded in empirical observation and this temporal dependence between trips for the same household results in a need to analyze both types of trips simultaneously.

Therefore, with the notable exception of Davies and Pickles' (1987) generalized model, the methods discussed above neglect to consider dynamic consumer behaviour variation and the full range of time dependencies which may occur in consumer purchasing (Section 2.1.6). Generally, these models are limited, focusing on parametric distributions for duration dependence which are more due to computational convenience than strong theoretical or empirical arguments. The functional form of duration dependence needs to be determined by the behaviour itself rather than be exogenously and arbitrarily defined by the analyst. This particular feature, which as subsequent sections indicate as the major focus of this research, should be viewed as an important generalization of current applied models of consumer behaviour since it allows the endogenous components of the process to determine the dynamic nature of the behavioural process. Assessment of the endogenous components of behavioural variation requires models which are based on purchase event histories so that learning and experience which influence observed choice processes are inherently considered in the analysis.

2.3 "Discrete–Choice" Modelling Approaches

The goal of "discrete–choice" modelling approaches is to quantify the relationship between observed choice decisions and the internal and external factors which govern the decision–making process, including choice alternative characteristics, individual characteristics and environmental factors (outlined in Sections 2.1.1 and 2.1.2). Discrete–choice models provide estimates of the probability that a choice (ie. purchase) will occur and are estimated from a sample of observed event outcomes made by individuals when confronted with a decision. In other words, observations are discrete events measured at low level, nominal (ie. categorical) or ordinal scales. A response (ie. purchase, choice, decision, event) can occur as an outcome of a dichotomous/binary decision situation in which only one of two possible alternatives is selected, or as a result of choice being made from multiple (polytomous) available alternatives. The literature concerning discrete–choice modelling is found in a number of disciplines, notably economics, psychology, engineering and geography (Hensher & Johnson, 1981; Wrigley, 1982). Generally, the emphasis of this literature is on the statistical requirements of discrete–choice models with limited concern for how well behavioural processes are represented by the 'random utility theory' underlying such discrete–choice models.

Section 2.3.1 reviews the random utility concepts underlying discrete–choice and Sections 2.3.2 and 2.3.3 examine the more commonly used discrete–choice models in dichotomous and polytomous choice scenarios, respectively, addressing their associated limitations and applications to spatial choice behaviour. Two main estimation procedures, least squares estimation and maximum likelihood estimation are used in discrete–choice modelling (see Ben–Akiva and Lerman (1985) and Domencich and McFadden (1975)). The dynamic elements of discrete–choice are described in Section 2.3.4 along with some advances that have attempted to generalize these models to include individual sources of behavioural variation.

2.3.1 The Theoretical Framework of Discrete–Choice

The concept of **random utility maximization**, developed in psychology and economics, provides a theoretical framework for discrete–choice modelling. Utility is a measure of the benefits associated with a particular alternative. Random utility maximization assumes that decisions are made by selecting the alternative with the highest utility. Theoretically, individuals are treated as active decision–makers (see Section 2.2.3) who recognize the utility of different alternatives. Intuitively, decisions are modelled so that each time a decision is made, a utility is randomly drawn from the distribution of possible utility values. Utility is modelled as being random because of observational deficiencies which largely result from measurement error and unobservable attributes, associated with both the alternative and the individual (Fischer & Nijkamp, 1987). Therefore, choice probabilities represent the analyst's statement of the probability that an individual will choose the utility–maximizing alternative from a limited and constrained set of discrete alternatives.

An alternative framework for discrete–choice modelling is provided by the concept of **constant utility**. The premise of this approach is that the utility associated with alternatives is fixed and a decision–maker is assumed to behave with a choice probability defined over the population as a distribution which is governed by utility parameterized alternatives. However, the constant utility approach is limiting because the validity of the choice axiom is dependent on the structure of the 'choice set' (see Ben–Akiva & Lerman, 1985, for details), and is more difficult to define, especially in the case of choice hierarchies. Consequently, the random utility approach dominates the discrete–choice modelling literature (Fischer & Nijkamp, 1987; 1985; 1983; Manski, 1981).

'Choice sets' refer to the mutually exclusive, collectively exhaustive alternatives faced by an individual in a decision–making process. The universal choice set assumption underlying discrete–choice models of stochastic behaviour holds that each decision–maker in a population faces the same set of alternatives at each decision point. This assumption can be particularly invalid in spatial choice decisions where individuals have spatially biased sets of alternatives (Fischer & Nijkamp, 1987; Haynes & Fotheringham, 1989; Wrigley, 1982). Moreover, decisions are typically made with limited knowledge of the alternatives, reflecting individual–specific search and information spaces. Manski (1981) suggests that this universal choice set assumption is innocuous because available alternatives unknown to a decision–maker can be identified by incorporating a zero value in the matrix which characterizes an individual's choice set. This solution, however, fails to consider, amongst other issues, the problem posed by alternatives which are also unknown to the analyst and Tardiff (1980) suggests a more useful approach would be to separate the alternatives which describe the choice set into those which are common to all members of the population from those which are individual–specific.

Theoretically, the 'maximizing' concept of utility oversimplifies the conflicting nature of complex choice decisions in which multiple choice criterion exist. For example, urban travel studies often examine trip linkages in isolation, focusing on the types, sequence or location of multi–purpose/multi–stop travel behaviour (Domenchich & McFadden, 1975; Kitamura, 1984; Kitamura & Kermanshah, 1984; Recker & Kostyniuk, 1978). Clearly, interaction and dependence occur between successive events in trip chains, resulting from tradeoffs between choice options and constraints. This argument parallels that of the active versus reactive decision–making tradition (discussed in Section 2.2.3) and is a major criticism of the discrete–choice modelling approach. Nijkamp et al. (1985) and Koppelman and Pas (1985) suggest replacing the 'maximizing' concept with a 'satisfier' notion, to help bridge this gap between reactive decision–making models and maximum utility choice behaviour theory. This 'satisfier' notion considers a hierarchy of choice alternatives within which decision–making is based on the selection of an alternative that most closely 'satisfies' the motivations underlying the decision process (see Nijkamp et al., 1985; Koppelman & Pas, 1985 for the methodological considerations involved). The 'satisfier' concept is intuitively appealing and may provide insight into the motivations underlying complex choice problems which are not addressed by maximum utility, but as yet, this concept is not mathematically operational and remains limited to conceptual modelling approaches.

A general discrete–choice modelling approach to decision–making behaviour requires three behaviour specifications: (i) definition of the choice problem and the alternatives available to the decision–maker (ie. the choice set); (ii) an evaluation of attributes associated with the alternatives (ie. the utility) and a decision rule for combining them; and (iii) a model of individual choice behaviour and a specified distribution representing the behaviour patterns of the population (Ben–Akiva & Lerman, 1985; Hensher & Johnson, 1981).

As an example of a decision problem in a discrete–choice framework, consider a consumer who decides to make a store visit to buy milk. The store alternatives are defined within the shopper's district, although he/she may not be aware of all the possibilities. If the available store alternatives are district superstores, supermarkets and local convenience stores, the shopper then evaluates the attributes associated with each alternative. Assume three attributes are associated with the stores: accessibility, (a), milk freshness, (m), and store friendliness, (f). Table 2.3.1 (page 85) depicts the information that would be available to the consumer. This information is processed by the individual who arrives at a choice of store by applying a decision rule – a specific sequence of evaluations. In a random utility maximizing framework, the information of Table 2.3.1 reduces to three utility values, U_1, U_2 and U_3, each associated with a store alternative. From these values the consumer then selects the store with the highest utility, ie. the store with the best combination of accessibility, milk freshness and store friendliness.

Table 2.3.1: Attributes of a store choice for milk buying

	Attributes		
Store choice	store accessibility	milk freshness	store friendliness
district stores	a_1	m_1	f_1
supermarkets	a_2	m_2	f_2
local stores	a_3	m_3	f_3

From a modelling perspective the probability of person n choosing alternative i is equal to the probability that the utility of i, U_{in}, is greater than or equal to the utilities of all other alternatives in the choice set, C_n. This may be written as:

$$P_n(i|C_n) = Pr(U_{in} \geq U_{jn}, \forall J \in C_n), \qquad (2.3.1)$$

where j corresponds to other alternatives. Choice probabilities are related to random utility maximization by assuming that each utility value is defined by the attributes.

Ben–Akiva and Lerman (1985) have identified distinct sources of randomness including unobserved attributes associated with alternatives, unobserved tastes and motivations of individuals, and measurement errors. Generally, total utility is expressed as the sum of both the observed and random components, thus equation (2.3.1) becomes:

$$P_n(i|C_n) = Pr(V_{in} + e_{in} \geq V_{jn} + e_{jn}, \forall J \in C_n), \qquad (2.3.2)$$

where: V_{in} and V_{jn} are the observable (or representative/systematic) components of utility i and j; e_{in} and e_{jn} are the unobserved (or disturbance/random) components of utility associated with alternative i and j. Definition of the observable components largely depends on the population being studied, the ability to segment the sampled population and the extent to which known (or assumed) attributes (which yield representative utility), can be measured (Hensher & Johnson, 1981). The random elements represent deviations from the 'group average' utility component and formulation of an operational discrete–choice model therefore requires explicit consideration of both the systematic component and these random components.

The systematic component of random utility can be characterized by two vectors. The first is a vector of attributes, $\mathbf{z}_{in}$, associated with the alternatives in the choice set and these attributes may vary over individuals; the second is a vector of attributes, $\mathbf{s}_n$, that characterize the individual decision–maker. Specification of V_{in} and V_{jn} thus becomes a matter of defining a combination of attribute vectors, $\mathbf{z}_{in}$ and $\mathbf{s}_n$, that reasonable approximate the systematic (or 'actual') effect on choice probabilities (Ben–Akiva & Lerman, 1985; Wrigley, 1981). The systematic component of utility i, which includes both $\mathbf{z}_{in}$ and $\mathbf{s}_n$, may be written in vector notation as:

$$\mathbf{x}_{in} = h\,(\mathbf{z}_{in}, \mathbf{s}_n)\ , \tag{2.3.3}$$

where h is a vector–valued function, specified to allow real transformations of the attributes, such as a logarithmic or exponential, to be valid for inclusion in the elements of $\mathbf{x}$. A commonly used functional form for the systematic component, V, (where $V = V(x_{in})$) is one which is linear in parameters. Ben–Akiva and Lerman (1985) stress that linearity in parameters is not equivalent to linearity in attributes, meaning that additive parameters do not necessarily imply that choice attributes are also additive (they could be multiplicative, for example) hence this assumption is less restrictive than one might think. If $\boldsymbol{\beta} = [\beta_1, \beta_2, ..., \beta_k]$ is a vector of k unknown parameters, then:

$$\hat{V}_{in} = \beta_1 x_{in1} + \beta_2 x_{in2} + ... + \beta_k x_{ink}\ . \tag{2.3.4}$$

The parameters $\beta_1, ..., \beta_k$ are assumed to be the same for all members of the population. If population groups exist and are believed to have entirely different β's, then it is possible to develop a model for each subgroup, a concept in consumer behaviour studies known as market segmentation. Models based on anything but individual–specific choice probabilities require some degree of aggregation and discrete–choice models are therefore aggregate models which only reflect truly disaggregate behaviour if each market segment corresponds to a single individual/household. Timmermans et al. (1984) examined the use of market segmentation and found that by disaggregating their sample of respondents according to their stated preferences into four categories, more accurate predictions of behaviour were obtained than if estimation was based on the sample population as a whole.

Traditionally, the random component of utility is specified as the difference $e_{jn} - e_{in}$. Consequently, the relative value of the random components associated with each alternative (as measured by their difference) is unaffected by the addition or subtraction of a constant to the systematic component (Ben–Akiva & Lerman, 1985), and so the mean of the disturbance term can be defined as equal to a constant without loss of generality. The mean of the disturbance component is often assumed to be zero and it's scale must be consistent with the systematic component (Hensher & Johnson, 1981). Once scaling is achieved, an appropriate functional form for the random disturbances is specified, such as a cumulative logistic or cumulative normal distribution. In practice, these distributions represent a combination of the sources of behavioural variation (Section 2.1.6) which influence the decision–making process and which are not included in the systematic component. Different choice models are produced by varying the assumed distributional form for the random component. The following sections discusses the dichotomous and polytomous choice situations and the most commonly used models in each. For notational convenience, discussion of choice situations is largely confined to a single individual's decision.

2.3.2 Dichotomous Choice Situations

In dichotomous choice situations, the choice set, C_n, is limited to two alternatives and binary values are commonly assigned to represent choice, having a value of 1 if chosen (ie. 'true') and 0 otherwise. Choice probability is typically assumed to be linear in parameters and attribute variables are assumed to be additive. The most commonly used binary discrete–choice model is the logit model which is based upon the logistic transformation of the choice probability, namely:

$$P_i = \frac{e^{\beta \mathbf{x}_i + \epsilon_i}}{1 + e^{\beta \mathbf{x}_i + \epsilon_i}}, \tag{2.3.5}$$

where: P_i is the probability of selecting alternative i where $0 \leq P_i \geq 1$, β is a vector of unknown parameters, $\mathbf{x}_i$ is a vector of attributes (utilities) associated with alternative i, $-\infty < \beta \mathbf{x}_i < +\infty$, and ϵ is an assumed distribution for the random component associated with alternative i.

The **logit** model is derived by taking the log of the ratio of the two probabilities based upon the logistic transformation, that is:

$$\log_e \frac{P_i}{P_j} = \log_e \frac{P_i}{1 - P_i} = \beta \mathbf{x}_i + \epsilon_i \,. \tag{2.3.6}$$

The left–hand side of equation 2.3.6 is a logit transformation, or the log odds (abbreviated L_{ij}), of choosing alternative i over alternative j. Logits are linear functions of the values of x and the model is nonlinear in terms of probabilities. The logit model allows for interaction among explanatory variables and can be specified to include an interaction term by introducing dummy variables into equation (2.3.6) (Hanushek & Jackson, 1977; Kohn et al., 1976; Markus, 1979; Theil, 1970; Wrigley, 1985; 1976; 1975). The predicted logit values,

$$\hat{L}_{ij} = \log_e \frac{\hat{P}_i}{\hat{P}_j} = \hat{\beta} \mathbf{x}_i \,, \tag{2.3.7}$$

are also unbounded but the predicted probabilities are restricted to the 0 to 1 range.

An important extension of the logit model is the beta–logistic model proposed by Heckman and Willis (1977) which examines population heterogeneity and provides estimates for both the probability of choosing a particular alternative and the distribution of choice probabilities over a population. The beta–logistic model is based on the assumption that no time dependence occurs and that exogenous variables are constant. However, heterogeneity is introduced by dividing the population into 'homogeneous' sub–groups within which each individual has the same values of exogenous variables. Probabilities within sub–groups are estimated with the logit model and the distribution of probabilities over the population is assumed to follow a beta distribution (see Heckman & Willis, 1977 for details). The beta–logistic has been applied successfully to studies of residential mobility (Davies & Pickles, 1984) and has been used to examine mode choice for grocery shopping trips (Uncles, 1987).

2.3.3 Polytomous Choice Situations

Polytomous choice means that a response (choice) is made when more than two alternatives (ie. $C_n \geq 3$) are considered. The logit model extended to examine multiple alternatives is specified in a **multinomial logit** (MNL) model and can be expressed as:

$$P_n(i) = \frac{e^{\beta_i x_{in} + \epsilon_{in}}}{1 + \sum_{j=1}^{J-1} e^{\beta_j x_{jn} + \epsilon_{in}}}, \qquad (2.3.8)$$

where: $j = 1,\ldots,J_n$, $\forall\, i,j \in C_n$, $i \neq j$. Note that the MNL model form is identical to the logistic transformation, equation (2.3.5), and reduces to the binary logit model when $j = 2$. The MNL is the most widely used multiple choice model despite the fact that it is based on restrictive assumptions that result in properties that are not always desirable (Ben–Akiva & Lerman, 1985; Haynes & Fotheringham, 1989; Hensher & Johnson, 1981; Wrigley, 1975; 1985). The MNL model has been successfully applied in urban transportation studies (a number of examples are provided by Ben–Akiva & Lerman, 1985; Domencich & McFadden, 1975; Yai, 1989), occupational attainment (Schmidt & Strauss, 1975a; 1975b) and college going behaviour (Manski, 1981). Applications are largely based on 'preference data', ie. records which are subjective accounts of preferred alternatives that are used to define utility values. Consumer behaviour studies include applications to mode choice for shopping trips (Domencich & McFadden, 1975), shopping strategies (Wrigley, 1975), and destination choice of shop visits (Moore, 1989; Recker & Kostyniuk, 1978).

The main assumption of the MNL model is the property of 'independence from irrelevant alternatives' (IIA). Essentially, IIA means that the probability ratio, that is the probability of choosing one non–zero alternative over another non–zero alternative, is unaffected by the presence or absence of any additional alternatives in the choice set. The IIA assumption is reasonable in situations where the choice set of alternatives concern distinctly different options which equally compete with all other alternatives in the choice set. However, if the attributes associated with alternatives are not independent the IIA property results in unrealistic choice predictions.

Say, for example, that initially only a superstore and suburban supermarket exist for buying milk. Suppose that a homogeneous sample of shoppers frequent both stores equally (ie. 50% of the market share visits each store). Imagine a new suburban store opens that is just as attractive to consumers as the other suburban store (ie. they have equal utility values). The market share of the superstore would remain at 50% since shoppers would continue to prefer it over the suburban stores, but the total utility value associated with the suburban stores would be the same and it is logical that the remaining market share would be equally divided between the two stores (ie. both suburban stores would each have 25% of the market share). However, this result would not be predicted by the MNL model whose estimates would predict that each store would have 33.3% of the market share (ie. the new store would be in equal competition/market share as the two pre–existing stores.

Therefore, when a distinct similarity between alternatives exists, the random component of utility is correlated. This in turn, violates the IIA assumption of equation (2.3.8). Consequently, alternative models which are flexible in dealing with cross–correlations among random variables are needed. The multinomial probit, nested logit and dogit models are three such alternatives and are comprehensively outlined in Hanushek and Jackson (1977), Pindyck & Rubinfeld (1976) and Wrigley (1985; 1982; 1981).

It should be noted that Tversky's (1972) elimination–by–aspects (EBA) approach provides an alternative conceptual strategy for discrete–choice modelling. The **EBA model** assumes a hierarchy in the choice process (as does the nested logit model) in which alternatives (each of which is viewed as having an associated set of aspects) are compared on the basis of a selected aspect and are eliminated from the choice set until a single alternative remains. A major flaw of the EBA model is its failure to ensure that the alternative that is retained is, in fact, superior to those which are eliminated (Tversky, 1972). Haynes & Fotheringham (1989) point out that despite the potential flexibility of these alternative polytomous discrete–choice models to model dependence between alternatives they have rarely been used as a means of accounting for spatial dependencies. The beta–logistic model of Heckman and Willis (1977) has been extended to examine polytomous choice situations to examine spatial choices of shopping centres (Dunn & Wrigley, 1983). However, spatial discrete choice inherently differs from aspatial discrete choice in that choice set alternatives are spatially dependent and both the alternatives and decision–makers are distributed and interrelated over space. Therefore, models which examine spatial choice decisions need to be generated within spatial choice theory along the lines of Fotheringham's (1989; 1988) version of a competing destinations model. Fotheringham's **competing destinations model** shares the hierarchical decision framework of the nested logit and EBA models, but recognizes that spatial alternatives perceived by an individual are not always distinct, which in turn, allows for continuous substitution between alternatives (see Fotheringham, 1989; 1988 for details).

2.3.4 Dynamic Discrete–Choice models

All of the discrete–choice models discussed thus far assume that influences on the choice of alternatives are all exogenous. In other words, these models assume unrealistically that the attributes generated by the process itself are not related to the behaviour process. An individual's information about choice alternatives depends on observation (and thus perception) made during the course of experience and learning, which result in a dependence of previous decisions on future choices. Therefore, a dynamic relation exists between choice information and decision–making behaviour in which the characteristics of the choice problem are influenced by the choice process itself. In other words, utilities associated with alternatives are also endogenously defined quantities and thus to fully explain consumer behaviour processes models must unite the dynamic aspects of behavioural variation with discrete–choice situations (Fischer & Nijkamp, 1987; Gensch, 1987; Richardson, 1982; Swait & Ben–Akiva, 1987).

Richardson (1982), for example, argues that choice set generation is a dynamic sequential process in which the final choice set is only known once the final decision is made. Richardson's (1982) search model is based on the premise that the search procedure, and hence choice set generation, depends on an individual's degree of prior knowledge about available alternatives, reasoning that persons with 'complete' prior knowledge have longer search processes than those with 'minimal' prior knowledge because they have greater awareness of the potential gain (ie. utility) associated with making a particular choice. Also, Richardson (1982) believes that individuals with less knowledge are more likely to accept alternatives with lower utility values because they are unaware of the potential gain associated with certain choices. Richardson's reasoning is, however, inconsistent with both the Howard and Sheth and EKB conceptual models (see Sections 2.1.4 and 2.1.5, respectively) which reason that limited prior knowledge leads to extended problem–solving tasks that consequently take more time because additional information is required to make a decision. It can be concluded from the conflicting reasoning of these models is that prior knowledge of alternatives influences both search processes and choice set generation, but the degree of this influence varies with different individuals. Gensch (1987) supports this claim in his dichotomous store choice study of Iowa farmers' fertilizer purchases. Gensch found that the sample segment with less prior knowledge were better represented by a hierarchical choice process whereas those with more knowledge about available alternatives (stores) were better represented by a simultaneous logit model (see Gensch, 1987 for details). Neither Richardson's (1982) nor Gensch's (1987) empirical analysis consider the influence of constraints on the generation of a choice set and constraints are likely to be an important component to choice set generation. However, their empirical evidence indicates that choice set generation is an endogenous process which exhibits individual variation that is due, at least in part, to past experience. Fully generalized models of consumer choice processes are therefore needed which simultaneously consider both the past history of the behavioural process and sources of population heterogeneity to fully explain observed consumer purchasing behaviour.

One of the earliest attempts to incorporate the influence of past choice history on choice probability estimates was proposed by Theil (1969) in his multinomial extension of the linear logit model. Theil (1969) explicitly defines the probability of an event in terms of explanatory variables and his model may account for interaction between attributes that describe choice alternatives. However, individual–specific sources of choice variation (ie. heterogeneity) occur (both observed and unobserved) which may not be identified by the analyst. Therefore, it is unlikely the model would contain all of the observed and unobserved exogenous attributes describing individual choice alternatives. Theil (1969) assumes that individual probabilities are continually updated based upon experience of alternatives. However, Theil's measure of 'experience' only accounts for aggregate change in choice probabilities from one time period to the next and can not distinguish between different (endogenous) sources of dynamic choice behaviour.

Dynamic discrete–choice models depend crucially on whether or not structural state dependence and/or 'spurious' state dependence are considered in model formulation (Manski, 1981). 'Spurious' state dependence occurs when population heterogeneity is omitted from choice behaviour estimates, resulting in a serial correlation effect which biases parameter estimates of observed variables. When this degree of serial correlation is unknown, previous experience may appear to influence future choice simply because it is a proxy for temporally persistent omitted variables which influence behaviour. On the other hand, 'true' state dependence (ie. structural state dependence, see Section 2.1.6) refers to actual time dependencies endogenous to the behavioural process. This distinction between 'true' and 'spurious' state dependence is discussed in more detail in Section 2.4.2.

Tardiff (1980) provides one of the first attempts to incorporate both 'true' and 'spurious' state dependence effects into a generalized discrete–choice methodology. Most spatial choice processes are repeated over time and this is especially evident in short–term destination choice processes, such as shopping. Tardiff (1980) regards recurrent choice behaviour as a sequence of static utility maximizing choices made by decision–makers whose utility functions may contain certain sources of both observed and unobserved heterogeneity. He proposes a utility function which explicitly accounts for the intertemporal nature of choice processes which may be written as:

$$U_{is}(t) = \mathbf{x}_{is}(t)\beta + \sum_j \varphi_{ij} C_{js}(t-1) + \tilde{e}_{is} + e^*_{is}, \qquad (2.3.9)$$

where subscripts i and j refer to alternatives, t to a time period and s to an individual. $U_{is}(t)$ is the utility of alternative i for decision–maker s at time t; $\mathbf{x}_{is}(t)$ is a vector of the systematic component of utility which may vary over time with β unknown parameters; φ_{ij} summed over all j allows the choice in one period to influence choice in the next period according to the value of $C_{js}(t-1)$, which is a lag term that equals one if the individual chooses alternative j in a previous time period and 0 otherwise; $\tilde{e}_{is}$ is an error term which refers to unobserved time–invariant effects; and $e^*_{is}(t)$ is an error term which varies over individuals and over time. The lag term, $C_{js}(t-1)$, therefore includes the influence of the most recent choice decision on current choice, ie. 'structural' state dependence. Furthermore, by setting different components of Tardiff's (1980) model to zero special cases of the model arise. For example, if $\mathbf{x}_{is}(t)\beta = 0$ the model reduces to a simple Markov model (Section 2.4.3) or if $\varphi_{ij} = 0$ and $\tilde{e}_{is} = 0$ for all i, j, and s then the model reduces to a static choice model, ie. one which is temporally independent (see Tardiff, 1980 for details). More recently, Davies (1984) and Davies and Pickles (1984) have considered structural state dependence in choice behaviour processes by extending the beta–logistic model to include a dynamic utility component as well as time–varying exogenous variables to examine the dynamic nature of residential mobility patterns.

2.4 "Feedback"/Adaptive–Behaviour Modelling Approaches

In their basic forms, discrete–choice models tend to consider purchase decisions/brand choices as being independent of previous choices although more recent developments in dynamic discrete–choice models are concerned with the influence of previous choices on current choice probability. Consideration of static choice behaviour essentially corresponds to the assumption of a 'Bernoulli–type' process in which the probability of choosing an alternative is constant over time. In a 'Bernoulli' process a consumer is assumed to have a constant probability of purchasing a particular brand (or equivalently, visiting a particular store) at time t, regardless of his/her purchasing decisions in the immediate or distant past.

However, observed purchasing behaviour is more complex than this and several modelling traditions have attempted to incorporate the influence of previous purchasing behaviour. These influences are known as *feedback effects* or *adaptive–behaviour* and encompasses the range of state dependence effects outlined in Section 2.1.6. Mathematical specification of feedback/adaptive behaviour in models of consumer purchasing has largely developed within the marketing research literature and models have been used to examine brand/store choice, brand switching and store loyalty behaviour (Aaker & Jones, 1971; Burnett, 1977; 1976; Cunningham, 1961; 1956; Ehrenberg, 1965; Frank, 1962; Harary & Lipstein, 1962; Lawrence, 1966; Lilien, 1974; Massy, 1966; Rao, 1969). These models have also been applied in transportation research (Burnett, 1978; 1974a; 1974b; 1973; Gilbert et al., 1972; Herniter & Magee, 1961; Lerman, 1979), and demographic studies (Ginsberg, 1979; Markus, 1979; McFarland, 1970; Spilerman, 1972). Furthermore, they have been generalized to account for the effects of population heterogeneity (Carman, 1970; Crouchley et al., 1982c; Enis & Paul, 1970; Massy et al., 1970; Massy, 1966; Tuma & Hannan, 1984) and nonstationarity (Lipstein, 1965).

2.4.1 Modelling Consumer Loyalty

Studies of brand/store loyalty represent the earliest attempts towards using probability models as tools to explain the pattern of consumer choices *directly* from observed behaviour. Brand/store loyalty can be broadly defined as the proportion of a household's (or individual's) total food purchases attributable to a particular brand/store during a specified period of time. Brown is identified as the first to examine brand loyalty behaviour in his classification of undivided, divided, unstable or non–loyal consumers, based on binary coded purchase sequences (Lawrence, 1966; Massy et al., 1970). Cunningham (1961; 1956), using data from the *Chicago Tribune* panel, also examined household loyalty, both to brands and to stores. Cunningham (1956) reports that 84% of all product purchases were attributable to a single brand in seven different product categories and that six shops were sufficient to account for over 90% of total household food expenditures (1961). The main findings of these authors indicate that households concentrate purchases on fewer brands and in fewer stores than would be expected if purchases/visits occurred in a purely random fashion. In other words, consumers exhibit a degree of loyalty.

Carman (1970) also found evidence of both brand and store loyalty using the Carman–Stromberg Entropy Loyalty Measure (CELM). The CELM is an index derived from the maximum likelihood ratio test of complete disloyalty assuming a zero–order multinomial model. Suppose a consumer has x number of shops to choose from (ie. the state space is x) and p_i is the proportion of purchases made at the i^{th} shop in a given interval of time, then complete disloyalty exists when $p_1=p_2=...p_x=1/x$ and under these conditions the CELM takes on the numerically largest value. Conversely, complete loyalty is defined as: $p_i=1$, $p_j=0$ for all $i \neq j$ and takes a minimum value of zero (see Carman, 1970). Carman used over 40 socio–economic and psychological characteristics to define variables to identify the 'best' predictors of the CELM. He concluded that the personal characteristics of consumers account for differences in the derived loyalty measures and that the single, most important predictor of brand loyalty is store loyalty. While Carman's results are by no means clear–cut, his study represents the most extensive examination of how individual characteristics influence loyalty behaviour (Charlton,

1973) and his findings provide strong argument for store choice decisions as the driving force behind repeat brand purchases which, in turn, implies that store switching behaviour is the most important exogenous determinant of repeat brand purchasing behaviour.

From the results of these pioneering studies, some conclusions may be made concerning the validity of Bernoulli–type assumptions when applied to consumer purchasing data. If brand/store choice behaved as a Bernoulli process there would not be any association between the number of previous purchases (visits) of a particular brand (to a particular store) and repeat purchase probability (ie. the process would be constant). Empirical evidence suggests that consumers, at least to some extent, exhibit loyalty towards brands/stores which, in turn, implies a positive association between past purchasing history and current purchasing probability. 'Loyalty measures' examine the repeatability of purchase sequences and from the findings cited above, it is apparent that consumer purchases are not independent, but rather produce non–random event sequences. Furthermore, the simple Bernoulli model assumes that individual characteristics have no influence on purchase probabilities (ie. the model assumes homogeneity). This assumption is not only intuitively unlikely, but must be considered suspect in light of empirical evidence which suggests otherwise (for example, see Aaker & Jones, 1971; Burnett, 1977; 1974a; Carman, 1970; Crouchley et al., 1982c; 1980; Enis & Paul, 1970; Frank, 1962; Rao, 1969).

A more formal approach to adaptive brand choice behaviour was considered by Kuehn in 1958 in his **Linear Learning Model** (LLM), a stochastic methodology originally developed in mathematical psychology (Massy et al., 1970). The LLM considers consumer decisions are affected by feedback acquired from previous purchase choices and consequently, purchase probabilities change each time a purchase decision is made. The act of purchasing and using a particular brand is assumed to influence the probability that that brand will (ie. positive–feedback) or will not (ie. negative–feedback) be purchased again and that the degree of influence (ie. feedback) increases the more recent the past decision. In the LLM, purchase–event feedback is operationalized in a 'feedback operator', which is a linear function of current choice probability (ie. the probability to repurchase) which incorporates a measure of the positive or negative effects which result from the purchase decision as a post–purchasing probability. Linearity in the feedback operator is not an unreasonable assumption in some situations, however, times exist when other functions may be more appropriate and the linearity assumption should not necessarily be adopted even when the feedback process appears to be linear in the probabilities (see Massy et al., 1970: 141 for details). Furthermore, the parameters of the LLM are assumed the same for all consumers which implies that the population is homogeneous with regard to the effects of feedback.

In his 1962 study, Kuehn examined the buying patterns of frozen orange juice purchases in 600 households of the *Chicago Tribune* panel and classified purchases of Snow Crop as "S" and all other brand purchases as "O". By aggregating all consumers with the same past purchasing histories, he applied a factor analysis approach and concluded that brand switching behaviour is higher than a zero–order process and at least the last four or five purchases affect current repurchase probabilities (Kuehn, 1962). Similarly, Rao (1969) found that Kuehn's historical weighting of past brand purchases holds for store choice behaviour and that the more recent and frequent a consumer visits a particular store, the greater the repurchase probability of visiting that store. Furthermore, Aaker & Jones (1971) advocate the LLM as a valid model for representing store choice behaviour, although they point out that the LLM's adequacy resides in appropriately defining store choice (see Aaker & Jones, 1971 for details).

On the other hand, Frank (1962) developed a counter–hypothesis and found that Kuehn's results for brand switching behaviour were attributable to population heterogeneity. Frank eliminated the influence of population heterogeneity by applying LLM model separately to the instant coffee purchases of 536 households in the *Chicago Tribune* panel. Frank's 'Household–Bernoulli' model assumes that each household has a single probability of buying a given brand and this probability remains constant over the period of study and he treats each purchase decision as an independent event. He concludes that a substantial part of the learning effects reported by Kuehn could be accounted for by individual differences in the initial probabilities (ie. population heterogeneity) and that the simple Bernoulli model fits the data quite well (Frank, 1962). In a re–examination of Kuehn's analysis, Massy et al. (1970) report that the existence of heterogeneity in initial probabilities did not cause any difference in this particular case and that the LLM provides good representation of brand switching behaviour for frozen orange juice patterns during the period under study.

2.4.2 Problems and Generalizations of Loyalty Models

Based on the work by Massy et al. (1970) it appears that the LLM may be more robust than previously believed, however, Frank's (1962) analysis brings to light an important issue in stochastic modelling approaches to consumer behaviour, that of the distinction between 'spurious' (ie. 'apparent') state dependence and 'structural' state dependence. 'Spurious' state dependence occurs when unaccounted for heterogeneity persists through time so that what appears to be the influence of state dependence is actually population heterogeneity (Heckman, 1981a; Massy et al., 1970; Reader, 1988; Uncles, 1985). For example, if individuals vary in their propensities to purchase Brand A and the characteristic differences associated with these individuals pervade over time, it may appear as though previous experience determines current choice probabilities when in fact it is individual differences governing probability estimates. On the other hand, 'structural' state dependence refers to the real influence of previous purchasing history on current or future probabilities. Failure to control for omitted heterogeneity components of the behavioural process may produce biased model parameters and identify negative duration dependence where none exists (Flinn & Heckman, 1982; Heckman & Singer, 1986: Wrigley, 1986).

The distinction between 'true' and 'spurious' heterogeneity may be used as an alternative explanation for the same pattern. Put simply, the 'spurious' effect of heterogeneity (a.k.a. 'contagion') occurs when differences between individuals appear to govern differences in individual probability estimates when it is actually 'structural' state dependence that accounts for these results, hence the apparent effect of heterogeneity is termed 'spurious'. For example, if a buying decision is considered independent of previous choices then the initial purchase of Brand A does not affect the probability that Brand A will be bought on a subsequent occasion. Furthermore, if the buying population is assumed to be homogeneous each individual has the same initial probability of purchasing Brand A. However, if homogeneity is assumed when the population is heterogeneous, repeat purchasing probabilities may appear to increase as the number of consecutive purchases of Brand A increase (ie. a state dependence effect) but this effect may simply be a function of selecting consumers with a high propensity of purchase Brand A on any given occasion (Allison, 1984; Frank, 1962; Lawrence, 1966; Massy et al., 1970). In empirical analysis, the distinction between spurious heterogeneity and spurious state dependence may not be easily distinguishable. For instance, in the classic field of accident studies it is often found that accidents occur in clusters (Massy et al., 1970). The question then becomes, are these clusters the result of some individual's being more accident–prone than others (ie. heterogeneity) or are they the result of one accident leading to another (ie. state dependence)?

In an attempt to examine the influence of population heterogeneity in a Bernoulli–type purchasing context, Morrison developed the Compound Beta Bernoulli model (see Massy et al., 1970: Section 3.5 for details). The Compound Beta Bernoulli model addresses individual differences by allowing the initial (or baseline) probabilities, p_0, of population members to follow a beta distribution while maintaining the Bernoulli assumption (ie. the model does not consider purchase–event feedback). The beta distribution appears sufficiently flexible to accommodate a variety of population purchasing patterns (for example, see Crouchley et al., 1982c; Massy et al., 1970) except when a large proportion of the population is composed of completely loyal (p=1) consumers and non–buyers (p=0). In other words, when observed purchasing patterns follow a bimodal distribution, a single beta distribution fails to adequately represent the data (Massy et al., 1970). This problem is apparent in Burnett's (1977; 1974a) application of the Compound Bernoulli model to store choice behaviour, where he consistently rejects the model since it fails to describe observation on the use of particular stores, different classes of stores and the behaviour of different population groups.

The influence of nonstationarity in consumer brand choice decisions is explicitly considered by Howard (1965) in his 'Dynamic Inference' model. In dynamic inference, a household is assumed to repeatedly draw it's purchase probability from a distribution, at randomly distributed points in time. In effect, the model assumes that households reevaluate the worth of different brands at discrete points in time, but the outcomes of successive evaluations are independent of one another and that purchase probabilities are constant between revaluations (ie. the process is Bernoulli) (see Howard, 1965; Massy et al., 1970 for details). The Dynamic Inference model considers the nonstationarity in consumer choice behaviour by including a reevaluation component to account for variation in consumer choice probabilities. However, this model neglects the influence of purchase–event feedback on the behavioural process.

2.4.3 Markovian Approaches

Examination of household switching patterns using Bernoulli–type process models provide insight to the sequence of brand (store) buying patterns but neglects the impact of purchase event feedback on purchase decisions. On the other hand, the LLM explicitly examines the influence of past purchasing history on buying probabilities. An alternative approach to examining the influence of purchase event feedback on buying behaviour is based on a simple or stationary first–order Markov process. In the simple Markov model, the probability of an individual experiencing an event which marks the transition to a new state or a renewal of the present state is a function of only the state currently occupied (continous–time) or last experienced (discrete–time). In continuous–time, an individual is considered to reside in a particular state until transition to an alternate, or renewal of the present, state occurs whilst, in discrete–time, the behavioural process follows a so–called Markov chain. Markov transition matrices are constructed from observation of the aggregate totals residing in each state at different points in time. Furthermore, the stationarity condition of Markov models means that the transition probability matrix (which holds for all individuals in the population) is independent of time and this causes long–term probability estimates to tend toward a steady state. This stationarity assumption is analogous to the 'no trend' condition of the NBD, BBD and Dirichlet models.

The simple Markov model has been used in studies which examine the behaviour sequencing of trip chains (Kitamura, 1983: Thill & Thomas, 1987), the sequencing of stop purposes (Kitamura, 1983), and the ordering of stop locations (Lerman, 1979). In general, however, these models may be inappropriate for trip–chaining analysis because the model assumes that travel decisions are made along the journey, whereas empirical evidence indicates that consumers plan their stops before embarking on a trip (Thill & Thomas, 1987). The simple Markov model has also been widely applied to examine brand purchasing and brand switching behaviour (see Ehrenberg, 1965; Harary & Lipstein, 1962; Herniter & Magee, 1961; Howard, 1963; Lipstein, 1975; Markus, 1979; Massy et al., 1970; Massy, 1966). However, these model applications generally make some rigorous assumptions, namely that of a first–order process, stationarity and homogeneity, which limit applicability.

The first–order assumption of simple Markov models means that the behavioural process is only influenced by the last or presently occupied state and the path taken to reach that state is considered irrelevant and so the process is said to be memoryless (ie. the independence of path assumption). Even though these models may provide useful representation of one type of adaptive behaviour, they obviously do not explain the full range of possible state dependence effects. In the marketing research literature, the simple Markov model has been generalized to consider n–order Markov processes where n previous decisions/choices influence the current decision/choice (see for example, Burnett, 1974b; Tuma & Hannan, 1984). The extension to n order processes is implied in the **Brand–Loyal** and **Place–Loyal models** developed by Massy et al. (1970), where a consumer tends towards a constant transition rate in which one alternative is habitually chosen (for empirical examples, see Burnett, 1978; Crouchley et al., 1982a; Pickles et al., 1981). However, past purchasing behaviour may have both positive and/or negative feedback effects shedding doubt upon whether or not constant transition rates are likely to occur in a consumer purchasing context.

There is no *a priori* reason why the assumption in simple Markov models of constant transition rates should apply in a consumer behaviour context. Furthermore, since these transition rates are assumed stationary, Markovian matrices converge rather rapidly to near steady state values (ie. a point at which probabilities are effectively constant). Although this can provide simple operational predictions of market share characteristics (Harary & Lipstein, 1962) it is not a realistic representation of behaviour. Moreover, the movement towards a steady state matrix necessarily implies that the corollary of transition rates diverging equally fact backwards through time should apply. However, when this is done, it is soon apparent that the matrices assume unreasonable values by including negative numbers or values which exceed the number of purchases (Ehrenberg, 1965:355).

Markovian applications are often applied in repeat–buying and brand switching studies. However, Massy (1966) found that, in such studies, individual transition matrices differ markedly from an aggregate matrix constructed from the population. He concludes that a Markov approach built up from individual transition matrices is more appropriate then one which assumes that individual consumers are homogeneous in a single aggregate matrix. Howard (1963) has noted that modelling each individual using the same aggregate transition matrix essentially represents a flow model and not a stochastic process.

2.4.4 Generalized Markov Models

Attempts to incorporate population heterogeneity into Markov–type processes takes two forms. The first form allows the baseline or initial probability associated with a particular choice alternative to vary across the population according to some specified functional form. This initial probability is in essence a theoretical notion in the sense that it represents the probability of choosing an alternative when no state dependence effects exist. As in the 'distributional–based' purchase incidence modelling tradition (Section 2.2.4) and the Compound Bernoulli model, the beta distribution has been a favored functional form for modelling population variation in baseline probabilities (Massy et al., 1970), although other mixing distributions have also been considered (see, for example, Crouchley et al., 1982a; Pickles et al., 1981). The second form of incorporating heterogeneity into Markovian models involves introduction of exogenous variables to account for individual characteristics, but this method has largely been confined to mathematical sociology rather than marketing research (McFarland, 1970; Spilerman, 1972; Tuma et al., 1979). Another generalization are the so–called latent Markov or lagged–latent Markov models which may be used when future transitions are assumed to be dependent upon an individual's previous propensities to occupy states, rather than their actual history of state occupations. The latent variable incorporates the notion of 'preference shifts' and, operationally, may serve to capture the changes in unobserved heterogeneity (Heckman, 1981a).

Markov models have also been generalized to incorporate the effects of duration dependence and nonstationarity. Recall that duration dependence is defined as the influence of the length of time spent in a particular state on future movement to an alternative, or a choice of the same state. In a 'renewal' situation, duration effects can be represented using the same distributional form between any two events. However, consumer purchasing is concerned with multiple event types and therefore, the form of duration dependence will vary between any pair of ordered states. These effects are formalized in Markov renewal or semi–Markov models (Coleman, 1981; Geyer & Wagner, 1988; Gilbert et al., 1972; Ginsberg, 1979; Heckman & Singer, 1986; Lerman, 1979; Seeber, 1984; Tuma & Hannan, 1984). Markov renewal models consider the assumed distributional form of duration dependence between each ordered pairs of states to exhibit stationarity whereas in semi–Markov models the assumed distributional form of duration dependence between each ordered pairs of states can reflect nonstationarity. Semi–Markov and Markov renewal models examine choice decisions operating in continuous–time but, as with the incorporation of exogenous variables, these models have been mainly applied in mathematical sociology. Empirical evidence indicate that nonstationarity is inherent in shopping behaviour (Broom & Wrigley, 1983; Guy et al., 1983; Uncles, 1985) and Lipstein (1965) presents a method for including nonstationarity using Markovian analysis to account for changes in consumer attitudes toward brand purchases.

2.5 Continuous–Time Event History Modelling Approaches

An alternative methodology which addresses both the dynamic nature of consumer behaviour and the influence of purchase event feedback on individual choice decisions within a single, unified framework is provided by continuous–time event history approaches to consumer behaviour. Modelling approaches to event history analysis have largely developed in biometrics, engineering and sociometrics, resulting in a collection of related methodologies which reflect the analysis of different types of events. Biometric studies typically examine survival data which is conventionally used in models which consider the length of time until an individual 'dies' under exposure to particular treatment regimes. In these studies an 'event' is synonymous with entrance into a defined terminating state. Biometric applications include the survival analysis of heart transplant recipients (Kalbfleisch & Prentice, 1980), child mortality studies (Trussell & Richards, 1985), and has become a standard method of analysis for cancer patients studies (Kalbfleisch & Prentice, 1980; Mode, 1980). Engineering applies the event history approach in "reliability" or "failure time" studies where the length of time until a system or component fails is of interest, 'failure' being analogous to 'death' in biometric terms (see Kalbfleisch & Prentice, 1980 for examples). Component failure (or death) also represents the occurrence of single, non–repeatable events since transition occurs to a final, absorbing state.

Although methods of handling survival data have been generalized within the above disciplines to event–history analysis of repeatable events, for example, the timing of births (Newman & McCulloch, 1984), it is in the fields of social science where both repeatable and multiple–types of events are the norm and where event–history methods come into their own. For example, event history methods have been applied in migration or settlement moves (Baydar & White, 1988; Davies et al., 1982; Odland & Bailey, 1990; Odland & Ellis, 1990), employment changes (Allison, 1984; Kiefer, 1988; Petersen, 1988; Tuma, 1982), and changes in socio–economic status (Allison, 1984; Flinn & Heckman, 1982; Tuma & Hannan, 1984; Tuma et al, 1979; Winship, 1986).

Allison (1984) reviews the event history literature and distinguishes between repeated and non–repeated events for both single and multiple types of events. This two–way classification effectively distinguishes, in the first case, the event history work in biometrics and engineering from that of social science and, in the latter case, the earlier event history work from more recent work. An example of multiple types of events occurs in the study of component failure, where it may be crucial to consider system failure due to the occurrence of different types of component failure as influencing total failure. Alternatively, in the study of the effectiveness of cancer treatments, it is obviously important to distinguish between deaths due to cancer from death due to other causes, whilst in a study of job terminations it may be necessary to separate voluntary from involuntary terminations. To accommodate different types of events, biostatisticans have developed so–called 'competing risk' models (Allison, 1984) and these are more attractive to social science where multiple events are the norm.

Consumer shopping behaviour is complex in that different types of purchasing events occur repeatedly over relatively short periods of time. Recognition of the multi–period, multi–state nature of individual purchasing behaviour has resulted in a need to acquire detailed individual purchasing histories. Longitudinal or panel data is data that follows a sample (or panel) of individuals over time, thereby providing multiple observation on each individual in the sample. Longitudinal data which records the number, timing and sequencing of events experienced by individuals is known as an *event history* (Allison, 1984; Coleman, 1981; Tuma & Hannan, 1984; Tuma, 1982).

Event history data of consumer purchases is ideal for examining shopping behaviour as it can provide observation on the characteristics of a buying trip every time a consumer makes a purchase choice and different kinds of events may be described by classifying observations into different event types. Event history data typically records the exact timing of individual purchase events, and this avoidance of temporal aggregation in data collection means such data is particularly well suited to studies of duration dependence in longitudinal data. Event history data is also appropriate to continous–time modelling approaches since purchase event histories are observed by retaining the same panel of individuals over time and thus the characteristic differences between individuals at the times of purchase may be recorded. In this way, event history analysis has the potential to identify individual sources of consumer behaviour variation (ie. population heterogeneity) which occur in multi–period, multi–state purchasing decisions.

2.5.1 Problems in Event History Data

Modelling of event history data typically encounters problems of *event censoring* and *initial conditions*, both of which may bias estimates of consumer behaviour variation. *Event censoring* occurs when the time until the first event (left–censoring) or the time until the event following the end of the observation period (right–censoring) is unkown (Allison, 1984; Blossfeld et al., 1989; Kiefer, 1988; Tuma & Hannan, 1984; Tuma, 1982). The consequences of event censoring depend on the model being estimated. If the probability of an event occurrence does not depend on time, censoring problems can be dismissed. However, if event probabilities are assumed dependent on the time since the last event then event censoring is a concern. For example, with commonly purchased grocery items, the probability of a purchase event occurring will likely depend on time since the previous purchase event and is related to the consumption pattern of the previously purchased goods (ie. inventory effects: see Section 2.2.4). Right censoring of event history data commonly occurs but is not as problematic as left–censoring because the left–censored observation has a backward relationship to past history on which no information exists whereas the right–censored observation is simply an unobserved extension of the observed process into the future (Tuma & Hannan, 1978). The degree of bias introduced by censoring depends upon the model assumptions with regard to state dependence but as the duration of the study period becomes long relative to the mean duration between events, the estimator bias becomes small (Flinn & Heckman, 1982). Consequently, if event history data is of sufficient length, censoring problems may be ignored, resulting in only a small loss of information and censored times, particularly left–censored observations, can be excluded from the analysis (Broom & Wrigley, 1983).

The *initial conditions* problem is related to that of left–censoring and occurs because the study period 'window' limits access to information on individual characteristics and the choice environment prior to the observation period. Therefore, the problem of initial conditions is essentially one of unobserved heterogeneity. If the underlying behavioural process is assumed to be in equilibrium (ie. it does not change over time), then the assumption of stationarity conditions reduces the problem associated with initial conditions but is not a complete solution. Furthermore, stationarity can be an unrealistic assumption in many applications, especially when time–varying exogenous variables are driving the behavioural process. Alternatively, it could be assumed that the relevant prior history is a truly exogenous determinant of the behavioural process (Heckman, 1981b). This 'prior history variable' can then be modelled by assuming it takes a particular distributional form, as is adopted for handling more general forms of unobserved heterogeneity in event history approaches (Wrigley 1986; 1985). Regardless of these solutions, the resulting bias in parameter estimates emanating from the initial conditions problem will depend on assumptions made about the process and also the length of the event history. The dependence of estimator bias on the length of the data set may result in non–comparable estimates for different data sets even when the same selection rule is employed for generating the data (Flinn & Heckman, 1982), a drawback common in regressional methods of longitudinal data (Allison, 1984; Kiefer, 1988).

2.5.2 Methods of Event History Analysis

Methods of event history analysis have developed independently within a number of disciplines resulting in a confusion of terminology for this field. Allison (1984) identifies three distinct dimensions that can be used to distinguish different approaches to event history data. The first of these is *distributional* versus *regression* methods. Early work in event history analysis focused on describing the distribution of time until an event or the distribution of individuals across different states. More recently, all disciplines have become concerned with explaining the cause of event occurrence and have used regression models which relate occurrence to a set of explanatory variables.

The second dimension is that of *parametric* versus *nonparametric* methods. Engineering and social science have tended to favor parametric approaches to event history analysis. These methods specify a particular distributional form for the timing between events, the most common being exponential, Weibull or Gompertz distributions. On the other hand, biostatisticans have adopted nonparametric methods that make few, if any, assumptions about the distribution of event times. Cox (1972) united these two approaches in a semi–parametric proportional hazards model. This model is semi– or partially parametric because it specifies a regression model with a specific functional form but is nonparametric insofar as the distribution of event times is not explicitly defined.

Allison's (1984) third dimension for event history data analysis is *discrete–* versus *continuous–time* methods, a distinction difficult to define with any degree of generality (Reader, 1988). The difference is essentially based on the relationship between the length of the observational time unit and the time scale of the process being studied. A discrete–time approach is adopted by many of the Markov models of Section 2.4.3, where transitions between states are considered to occur at specific intervals in time. Alternatively, when the time of an event occurrence is measured precisely, continuous–time methods may be employed. In continuous–time, an individual is considered to reside in a particular state until a transition to another state occurs.

Discrete–time models have traditionally been the preferred choice of social scientists, reflecting the fact that data came in discrete form and analogies could be drawn with familiar cross–sectional models (Uncles, 1988). However, for the occurrence of many events, no natural time unit for observation exists and forcing data to conform to the arbitrary intervals of surveys may conflict with the natural state of the behavioural process. Consequently, a major drawback of discrete–time models is that parameter estimates are specific to the particular time unit of analysis. Therefore, continuous–time models are generally preferred due to their analytical convenience, being invariant to the time unit used in the empirical work. For example, typical consumer panel surveys may record the number of times an individual visits a particular store and the data may be considered complete.

However, insight into the causal mechanisms of the process may be limited if observation is restricted to discrete points in time. These causal mechanisms may include dependencies in the sequencing of shop visits (ie. choices), nonstationarity caused by variation in the day of the week or the time of day of the trip and intra–week duration effects (Reader, 1988). Knowledge that individuals experience events, such as shop visits, at any point in time requires monitoring the purchasing process in continuous–time so that all such event occurrences can be identified. Thus, from a theoretical standpoint, it is more realistic to regard behavioural processes as acting in continuous–time rather than sporadic discrete–time.

2.5.3 Continuous–Time Models in Event History Analysis

Continuous–time models in event history analysis examine the probability that an individual residing in a particular state, at a particular time, will leave that state after a certain duration. For example, in a study of store switching behaviour it may be of interest to examine the probability that a consumer will switch from store A to store B at a certain point in time, given that the individual has shopped only at store A for a specified length of time. It may be useful to specify such situations in terms of conditional probabilities, thereby utilizing the information that duration of time spent shopping at store A can influence the probability of visiting store B.

In this example of store switching, a switch represents the occurrence of an event and switches are separated in time by *spells* or *episodes* in which no change in state (ie. store visited) occurs. The probability of switching stores thus may be viewed as being conditional on the timing and state of the previous store visit and the value of this probability will change with duration from that visit. More complex models based on conditional probabilities may consider lagged duration effects and so view an event as the outcome of a sequence of episodes thus taking full advantage of information contained in event history records.

The statistical models of event history analysis take as their basic observation the length of time intervals (ie. durations) between consecutive events, ie. changes in state. Events are defined by some qualitative dependent variable and therefore represent changes in the set of distinct values defined by the *state space* of the process, where *state space* refers to a finite set of mutually exclusive and collectively exhaustive choice alternatives. If the durations can be measured exactly, then the point of time at which a change of state occurs can be represented by a stochastic process with a continuous–time parameter.

In a statistical model, points of time at which transition occurs are represented by $0 = T_0 \leq T_1 \leq T_2 \leq \ldots T_k$, the states of the process are represented by Y_0, Y_1, Y_2, ...,Y_k, (where k = 0,1,2,...), and thus the corresponding stochastic process (Y_k, T_k) may be described as:

$$Z = \{Z(t)\colon t \geq 0\}\ , \qquad (2.5.1)$$

where $Z(t) = Y_{k-1}$ for $T_{k-1} \leq t \leq T_k$, k = 1,2,... and equation (2.5.1) is a continuous–time, discrete state stochastic process.

Continuous–time models originated in methods designed to examine single events of one type (for example, alive to dead) in which the qualitative variable takes on one of two possible values, and it is to this type of event that discussion will be initially confined. Nearly all continuous–time, discrete state models (referred to hereafter as simply continuous–time models) share the notion of the *hazard rate* as the fundamental dependent variable in model specification. The '*hazard*' is the conditional probability that an individual will experience the event during a particular time interval, from t to ∇t, given the individual was at risk (ie. had not yet experienced the event at time t). If this probability is divided by the length of the time interval, which tends toward zero (ie. occurs over infinitesimally small time intervals), then a continuous–time *hazard rate*, $h(t)$, is defined:

$$h(t) = \lim_{\nabla t \to 0} Pr\,(t \leq \mathrm{T} < t + \nabla t | \mathrm{T} \geq t)/\nabla t\,. \tag{2.5.2}$$

It is important to note that hazard rates are not (conditional) probabilities, rather the hazard rates are similar to probabilities in that they are necessarily positive, being the limits of the ratio of two positive quantities, but unlike a probability, hazard rates can be greater than unity.

The hazard rate is equivalent to the conditional likelihood of an event occurring at t for those individuals whom have not yet experienced an event. This is made apparent by noting that the hazard is equal to:

$$h(t) = \frac{f\,(t)}{1 - F\,(t)}\,, \tag{2.5.3}$$

where the numerator is the probability density function (p.d.f) and the denominator is one minus the cumulative distribution function, $F(t)$. The probability density function can be written as:

$$f\,(t) = \lim_{\nabla t \to \infty} Pr\,(t \leq \mathrm{T} < t + \nabla t)/\nabla t\,. \tag{2.5.4}$$

The survivor function is the probability that the random variable T will equal or exceed the value of t and is, in turn, equal to one minus the cumulative distribution function, $F\,(t)$. That is,

$$S\,(t) = Pr(\mathrm{T} \geq t) = 1 - F\,(t), \tag{2.5.5}$$

where:

$$F\,(t) = P\,(T < t), \tag{2.5.6}$$

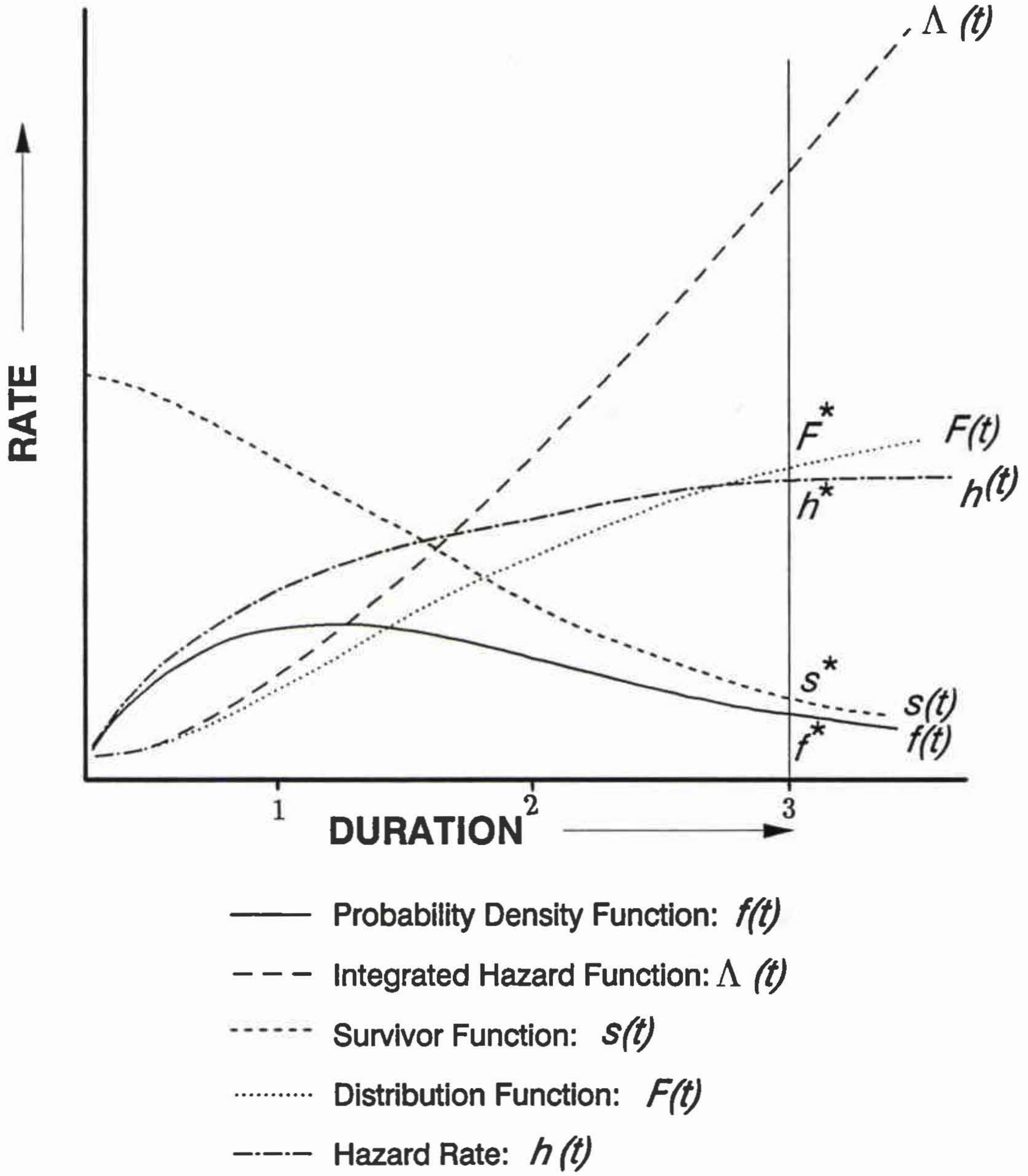
which gives,

$$h(t) = f\,(t)/S\,(t)\,. \tag{2.5.7}$$

Note that specification of the hazard rate for a process defines the survival rate and vice versa and equation (2.5.7) is simply an alternative specification of equation (2.5.3).

The distribution of T can be described by $f\,(t)$, $S\,(t)$ or $F\,(t)$ and Figure 2.5.1 (page 117) illustrates the relationship between these different functions. According

Figure 2.5.1: The hazard rate and other functions



(source: Kiefer, 1988:650)

to the Figure, the probability that a spell lasts less than three time periods is F^*, or equivalently, the probability of a spell lasting three or more periods is S^*. The probability that a spell will end between three and three plus ∇ periods is $f^*\nabla$, while the probability that a spell ends between three and three plus ∇ periods, conditional on having lasted three periods, is $h^*\nabla$. The integrated (or cummulative) hazard function ($\Lambda(t)$) is defined as:

$$\Lambda(t) = \int_0^t h(u)\,du\,, \tag{2.5.8}$$

and is neither a probability nor does it have an intuitive interpretation (Kiefer, 1988). The integrated hazard function is, however, a useful for tool in a variety of model specification checks and is related to the logarithm of the survivor function,

$$\hat{\Lambda}(t) = -\ln\,[S(t)]. \tag{2.5.9}$$

Equation (2.5.3) and (2.5.7) indicate that one can define the hazard rate for any variable if its probability density function is known (and consequently, its cumulative distribution function would also be known). The hazard rate may be viewed as the 'speed' with which an individual approaches a particular transition or alternatively, the 'speed' with which a spell will be completed. The hazard can capture the notion that individuals may differ in their hazard rates, where individuals with large hazard rates are more likely to undergo transitions earlier, whilst those with small hazards are likely to experience transitions later (Kiefer, 1988; Winship, 1986). The hazard rate can also provide a useful definition of duration dependence. From equation (2.5.9) it follows that:

$$\hat{h}(t) = -d\ln S\,(t)/d\,(t)\,. \tag{2.5.10}$$

Positive duration dependence exists at t^* if $d\hat{h}(t)/dt > 0$ at $t = t^*$. The hazard rate of Figure 2.5.1, exhibits positive duration dependence at all t. Positive duration dependence means that the probability that a change in state will occur increases as the length of the spell increases (ie. an increasing hazard rate exits). Conversely, negative duration dependence exits at t^* if $d\hat{h}(t)/dt < 0$ at $t = t^*$. Negative duration dependence means that the probability that a change in state will occur decreases as the length of the spell increases (ie. a decreasing hazard rate). In terms of the store switching example, a consumer who may become increasingly bored with shopping only at store A and, as a result, has an increasing probability of switching to store B as time progresses would exhibit positive duration dependence. On the other hand, if continued shopping solely at store A made the customer feel more comfortable as he/she became more familiar with pricing, store layout, service staff, etc... then the probability of switching to store B would decrease over time, resulting in negative duration dependence.

Two main methods of continuous–time hazard rate model construction currently dominate the event history literature, namely the fully parametric and the partially parametric approach. In principle, each approach can be used to accommodate duration dependence, but, in practice, a particular strategy may seem more congruent with some forms of duration dependence than with others (Kiefer, 1988; Tuma & Hannan, 1984). A fully parametric (or simply, parametric) approach to duration dependence requires a parametric distributional form to describe the nature of duration dependence. On the other hand, the partially parametric approach makes no a priori assumption regarding the way duration dependence influences behaviour. The remainder of this section discusses these two different modelling approaches in the context of continuous–time models and the attempts made in the consumer behaviour literature to develop fully generalized models. For a more detailed description of these modelling approaches see, for example, Kalbfleisch and Prentice (1980).

2.5.4 The Fully Parametric Approach

In a fully parametric event–history model a parametric distributional form is assumed for the baseline hazard rate, $h_0(t)$. This then defines a distributional form for the 'time until event occurrence' (ie. duration), T. One of the most widely used parametric models assumes that the instantaneous hazard rate is independent of time. In other words, it it assumed that no duration dependence exists:

$$dh(t)/dt = 0 \;, \tag{2.5.11}$$

which, in turn, implies a constant hazard rate:

$$\hat{h}(t) = \lambda \;, \tag{2.5.12}$$

A constant hazard rate gives rise to an **exponential** distribution for 'time until event occurrence'. The exponential distribution is a one parameter distribution with $\lambda>0$ and is often called memoryless because the conditional probability of experiencing an event (in a time interval of specified length) is the same regardless of how long the individual has been at risk (Allison, 1984; Flinn & Heckman, 1982; Heckman & Singer, 1986; Kalbfleisch & Prentice, 1980; Kiefer, 1988). Equation (2.5.12) indicates that the exponential distribution is uniquely characterized by the value of the hazard function itself. The corresponding estimates for the survivor and density functions are:

$$\hat{S}\,(t) = \exp\,(-\lambda t) \tag{2.5.13}$$

$$\hat{f}\,(t) = \lambda\,\exp(-\lambda t). \tag{2.5.14}$$

Since the exponential distribution is defined by a single parameter, λ, the family of distributions obtained by varying λ is not very flexible. Consequently, the exponential model is unlikely to be adequate if model data contains individuals who, for instance, possess very long and very short duration times. Numerous alternatives to the exponential distribution can be used to describe 'time until event occurrence', such as the gamma distribution, log–normal distribution, generalized F distribution, inverse Gaussian distribution, as well as generalizations and combinations of any of these (see Cox, 1972; Kalbfleisch & Prentice, 1980; Tuma & Hannan, 1984 for details). The remainder of this discussion focuses on four of the more commonly used alternatives to the exponential distribution.

The **Weibull** distribution is a simple but important generalization of the exponential distribution. The Weibull is a two parameter distribution with $\lambda > 0$ and $\alpha > 0$ and simplifies to the exponential when $\alpha = 1$. The form of the duration dependence depends on α (α being the shape parameter for T), therefore, the Weibull model parameters, λ and α, can be considered as affecting the location and the scaling of the distribution of 'time until event occurrence', respectively (Kalbfleisch & Prentice, 1980; Kiefer, 1988; Tuma & Hannan, 1984). The Weibull distribution of 'time until event occurrence' has a hazard functional form of:

$$\hat{h}(t) = \lambda\alpha\,(\lambda t)^{\alpha-1}\,. \tag{2.5.15}$$

A monotone increasing hazard rate of the Weibull model exists if $\alpha > 1$, a monotone decreasing hazard if $\alpha < 1$ and a constant hazard rate if $\alpha = 1$. Also, the logarithm of the Weibull hazard rate has a linear dependence on the log of time,

$$\ln \hat{h}(t) = \ln(\lambda\alpha) + (\alpha - 1)\ln(\lambda t). \tag{2.5.16}$$

The expressions for the Weibull estimates of the survivor and density functions are:

$$\hat{S}(t) = \exp(-\lambda t^{\alpha})\,, \tag{2.5.17}$$

$$\hat{f}(t) = \lambda\alpha\, t^{\alpha-1} \exp(-\lambda t^{\alpha})\,. \tag{2.5.18}$$

The **Gompertz** is another commonly used alternative to the exponential or Weibull model. Assuming a Gompertz distribution for 'time until event occurrence, T, the Gompertz hazard rate may be expressed as:

$$\hat{h}(t) = \lambda_0\, e^{\delta t}\,. \tag{2.5.19}$$

In the Gompertz model the log of the hazard increases or decreases linearly with time, ie:

$$\ln \hat{h}(t) = \ln \lambda_0 + \delta t\,, \tag{2.5.20}$$

where δ is a positive or negative constant. The survival and density functions associated with the Gompertz model are

$$\hat{S}(t) = \exp\,[(-\lambda_0/\delta)(e^{\delta t}-1)] \tag{2.5.21}$$

$$\hat{f}(t) = (\lambda_0 e^{\delta t}) \exp\,[(-\lambda_0/\delta)(e^{\delta t}-1)] \tag{2.5.22}$$

Both the Gompertz and Weibull models relax the constant hazard assumption of the exponential model, allowing for the hazard to increase or decrease with time. However, none of the models discussed thus far allow for the hazard rate to change direction over time, for example, by initially increasing but then later decreasing over time. The **log–logistic** is a nonmonotonic distribution which accommodates this type of changing hazard function. The log–logistic model is often specified in terms of log T, rather than the hazard rate, in order to facilitate the inclusion of explanatory variables into the equation (Kalbfleisch & Prentice, 1980). The log–logistic is a two parameter distribution with λ and α greater than zero. By letting $Y = \alpha^{-1}$ and $v = -\ln \lambda$, the log–logistic model can be written as:

$$\ln T = \frac{Y^{-1} \exp[(t-v)/Y]}{\{1+\exp[(t-v)/Y]\}^2} . \qquad (2.5.23)$$

The hazard, survivor and density functions of the log–logistic model are:

$$\hat{h}(t) = \frac{\lambda\alpha \ (\lambda t)^{\alpha-1}}{1+(\lambda t)^{\alpha}} \qquad (2.5.24)$$

$$\hat{S}(t) = \frac{1}{1+(\lambda t)^{\alpha}} \qquad (2.5.25)$$

$$\hat{f}(t) = \frac{\lambda\alpha \ (\lambda t)^{\alpha-1}}{[1+(\lambda t)^{\alpha}]^2}, \qquad (2.5.26)$$

respectively. The log–logistic is monotone decreasing from infinity if $\alpha < 1$ and monotone decreasing from λ if $\alpha = 1$.

Alternatively, a log–normal distribution may be assumed for the 'time until event occurrence, T, resulting in the **log–normal** model which also possesses a nonmonotonic hazard rate. Again, letting $\mathrm{Y} = \alpha^{-1}$ and $v = -\ln \lambda$, the log–normal model can be written as:

$$\ln T = (2\pi)^{-0.5} \exp[-\{(t-v)/\mathrm{Y}\}^2 / 2]. \qquad (2.5.27)$$

The corresponding estimates for the hazard, survival and density functions of the log–normal model are:

$$\hat{h}(t) = f(t) \ / \ S(t) \qquad (2.5.28)$$

$$\hat{S}(t) = 1 - \phi(\alpha \ln \lambda t) \tag{2.5.29}$$

$$\hat{f}(t) = (2\pi)^{-0.5}\alpha t^{-1}\exp[\{-\alpha^2(\ln\lambda t)^2\}/2] \tag{2.5.30}$$

where ϕ (z) is the standard normal distribution function. The hazard function has a value of 0 at t=0, increases to a maximum and then decreases, approaching zero, as t becomes large. The log–logistic hazard resembles the log–normal hazard if $\alpha > 1$, increasing from zero to a maximum at $t = (\alpha - 1)^{\alpha - 1}/\lambda$ and then decreasing thereafter (hence forming an inverted U–shape). The log–logistic distribution provides good approximation to the log–normal distribution except in the tails of the distribution, where the former distribution is slightly heavier in the tails than the latter. However, the log–logistic model is more convenient for handling censored data than the log–normal model because it possesses simpler algebraic expression for the hazard and survivor functions (Kalbfleisch & Prentice, 1980).

Although the specification of parametric models is fairly straightforward, the difficulty in continuous–time event history models arises in their estimation, especially if the data contains censored observations. Statisticians developed maximum likelihood procedures for estimating the exponential model in the late 1960's (Allison, 1984) which was soon followed by extending maximum likelihood to other models. As a result, maximum likelihood estimation (MLE) has become standard procedure for parametric model estimation and consequently is available in most event history software packages, including LIMDEP and SURVREG the software packages used in this research (see Section 3.4 for description). Blossfeld et al. (1989:71) give a detailed description of MLE but the general properties of MLE are noted here. First, ML estimators possess excellent asymptotic properties in large samples under fairly general conditions for the probability distribution function of the random variable (Allison, 1984; Blossfeld et al., 1989; Tuma & Hannan, 1984; Tuma et al., 1979). In other words, as the sample/panel size becomes infinitely large, ML estimates are unbiased, normally distributed and have minimum variance (ie. are efficient). Therefore, as long as the model assumptions hold, MLE can be relied upon to produce good estimates in a sufficiently large sample. Second, MLE can combine both censored and uncensored observations in the parametric estimation, thereby avoiding bias that results from more ad hoc procedures that have been designed to cope with censoring (described in Tuma & Hannan, 1984). Third, the computational requirements of MLE are no more difficult or costly than other methods, such as OLS or moment estimation, in the context of continuous–time stochastic models. OLS and moment estimation have been developed to deal with censored data (Tuma & Hannan, 1984) but such methods are not readily available.

2.5.5 Generalizations of the Fully Parametric Approach

The use of covariates (ie. explanatory variables) to account for behavioural variation due to heterogeneity has been one of the most significant generalizations of continuous–time event history modelling. The inclusion of covariates in continuous–time event–history modelling leads to the regression–based event history approaches. As mentioned in Section 2.5.2, regression–based approaches are replacing the distributional–based approaches. The sign of the regression coefficient(s) indicates the directional effect explanatory variables have on the likelihood of a spell ending. Inclusion of covariates is also important to the identification of 'structural' state dependence from that of 'spurious' state dependence. Two general classes of continuous–time models which inherently incorporate covariates dominate the event history literature, namely accelerated failure–time models and proportional hazards models.

Accelerated failure–time models assume heterogeneity enters as a direct transformation of time by altering the time scale of the behavioural process by a specified multiplicative factor (Allison, 1984; Blossfeld et al., 1989; Kalbfleisch &

Prentice, 1980; Kiefer, 1988; Winship, 1986). In other words, these models assume a base–line hazard rate, h_0, exists and the effect of covariates (or regression variables) is to alter the rate at which an individual proceeds along the time axis, accelerating (or decelerating) the 'time until event occurrence', T. For example, let T > 0, and $\mathbf{x} = (x_1,...,x_n)$ represent a vector of explanatory variables (ie. covariates) that have been observed (such as, individual income, employment status or household size). Specifying $\Psi(\mathbf{x})$ as a function of these covariates, the hazard rate, survivor and density functions can be defined as:

$$\hat{h}(t\,;\mathbf{x}) = h_0[t\,\Psi(\mathbf{x})]\;\Psi(\mathbf{x}) \qquad (2.5.31)$$

$$\hat{S}\,(t\,;\mathbf{x}) = S_0[t\,\Psi(\mathbf{x})] \qquad (2.5.32)$$

$$\hat{f}\,(t\,;\mathbf{x}) = f_0[t\,\Psi(\mathbf{x})]\;\Psi(\mathbf{x})\;, \qquad (2.5.33)$$

where $\hat{h}(.)$, $\hat{S}(.)$ and $\hat{f}(.)$ refer to the standard conditions of $\mathbf{x} = 0$ and $\Psi(0) = 1$, and h_0, S_0, and f_0 represent the constant baseline functions. In terms of 'time until event occurrence', the random variable, T is:

$$\mathrm{T} = \mathrm{T}_0/\Psi(\mathbf{x})\;, \qquad (2.5.34)$$

where T_0 corresponds to the baseline conditions. If we let $\alpha = \mathrm{E}(\log\,\mathrm{T}_0)$, then equation (2.5.34) may be written as:

$$\ln\mathrm{T} = \alpha - \ln\Psi(\mathbf{x}) + \epsilon\;, \qquad (2.5.35)$$

where ϵ is an error variable independent of $\mathbf{x}$ and with zero mean distribution. Thus to define $\Psi(\mathbf{x})$ parametrically, a term $\Psi(\mathbf{x}\;;\,\boldsymbol{\beta})$ needs to be defined, where $\boldsymbol{\beta}$ is a vector of parameters. The most natural choice for $\Psi(\mathbf{x}\;;\,\boldsymbol{\beta})$ is:

$$\Psi(\mathbf{x}\;;\,\boldsymbol{\beta}) = \mathrm{e}^{\boldsymbol{\beta}\mathbf{x}}\;, \qquad (2.5.36)$$

(Blossfeld et al., 1989; Kalbfleisch & Prentice, 1980; Reader, 1988; Winship, 1986). From this, equation (2.5.36) may be simplified to:

$$\ln\mathrm{T} = \alpha + \boldsymbol{\beta}\mathbf{x} + \epsilon\;. \qquad (2.5.37)$$

Therefore, equation (2.5.37) is a log–linear regression model with error variable ϵ having a specified distribution (which has a mean of α). Different members of the accelerated–failure time model class arise depending on the parametric form specified for ϵ. If ϵ is specified by a standard extreme value distribution then the exponential distribution for T is obtained. Other commonly specified distributions for ϵ include: the normal, log–gamma, logistic and extreme value distributions which result in the log–normal, gamma, log–logistic and Weibull distributions for T, respectively (Allison, 1984; Blossfeld et al., 1989; Kalbfleisch & Prentice, 1980).

Proportional hazards models represent another class of regression–type models in which the effect of covariates is to multiply the hazard function itself by a scale factor. The proportional hazards model is so named because at anytime, t, the ratio of the hazards between two individuals (ie. covariate settings) is constant. In other words, any two individuals who are characterized by different covariate values have corresponding hazard rates that are proportional. In proportional hazards models, the constant vector, $\mathbf{x}$, of covariates (ie. explanatory variables) is incorporated as:

$$\hat{h}(t\,;\mathbf{x}) = \Psi\;(\mathbf{x})\,h_0(t)\,, \tag{2.5.38}$$

where $h_0(.)$ is the baseline hazard under the standard conditions of $\mathbf{x} = 0$ and $\Psi(0) = 1$. If $h_0(t) = \lambda$, equation (2.5.38) reduces to the exponential model and when $h_0(t) = \lambda\alpha\;(\lambda t)^{\alpha-1}$equation (2.5.38) becomes the Weibull model. Thus both the exponential and Weibull models can be generalized to regression models by allowing the hazard rate to be a function of covariates, $\mathbf{x}$. The exponential and Weibull are the only models which are both proportional hazards models and accelerated failure–time models. When $\mathbf{x}$ acts multiplicatively on the hazard rate the exponential and Weibull are proportional hazards models; when $\mathbf{x}$ acts multiplicatively on T itself (ie. acts additively on Y), then both of these models become log–linear, accelerated failure–time models.

Parametric estimation of the proportional hazards model is achieved through MLE by specifying a distributional form for h_0 and a functional form for $\Psi(\mathbf{x})$. The most common function chosen for $\Psi(\mathbf{x})$ is:

$$\Psi(\mathbf{x}\,;\,\beta) = e^{\beta\mathbf{x}}\,, \tag{2.5.39}$$

where the log of the hazard rate is a linear function of covariates. Note that equation (2.5.39) is the same as for the accelerated failure–time model class, equation (2.5.36). Frequently, $h_0(t)$ is parametrically specified to produce an exponential, Weibull or Gompertz distribution for 'time until event occurrence', T.

The accelerated failure–time models and the proportional hazards model represent generalizations over simple distributional models by incorporating covariates. The accelerate failure–time models restrict the transformation of duration time but allow fairly general error distributions to be specified. The proportional hazards models, on the other hand, restrict the distribution of the error term but allow fairly general transformations of durations (to achieve linearity in the explanatory variables) (Kiefer, 1988). Thus the choice between these two types of models generally resides in the focus of interest and data availability in a particular study (Allison, 1984).

2.5.6 The Partially Parametric Approach

In the parametric models, continuous time hazard rates are estimated using MLE which requires that the baseline hazard rate, $h_0(t)$, be a specified distributional form. On the other hand, the $h_0(t)$ need not be so specified if partial likelihood estimation (PLE) is used. Cox (1972) developed the PLE procedure for proportional hazards models, giving rise to the partially (or semi–) parametric proportional hazards model (a.k.a. **Cox's** proportional hazards model). Mathematical details of PLE are given in Allison (1984:67), Blossfeld et al. (1989:73) and Kalbfleisch and Prentice (1980:27), but some of the general properties are worth noting. PLE relies on the fact that the likelihood function for Cox's (1972) model can be factored into two parts, one which contains information only on the coefficients expressed in β; and one which contains information about both β and the baseline hazard function. PLE ignores the second factor and treats the first factor as though it were an ordinary likelihood, that is, it only depends on the order in which events occur and not the exact times of the occurrences. The resulting estimates are both asymptotically unbiased and asymptotically normally distributed, although they are not fully efficient because information is lost when the exact event times are ignored. Allison (1984) argues that this loss of efficiency is usually so small so as not to be a concern. However, this loss of information may be important if the study is concerned with explicitly identifying the dependence of the hazard function on duration.

The hazard rate of Cox's proportional model may be written as:

$$\hat{h}(t;\mathbf{x}) = h_0\,(t)\,\exp\,(\mathbf{x}\beta)\,, \qquad (2.5.40)$$

where $\mathbf{x}$ is a vector of covariates, acting multiplicatively on the hazard rate; β is the corresponding parameter vector; and $h_0(t)$ is an arbitrary, unspecified baseline hazard rate. The proportionality of the hazard rates means that for any two individuals the ratio of their hazard functions is independent of time, t (ie. the same meaning as in the parametric proportional hazards models of Section 2.5.4). This assumption of proportionality limits the potential applications of Cox's model (Blossfeld et al., 1989; Kalbfleisch & Prentice, 1980) but two generalizations of the model are possible which increase its applicability without substantially complicating estimation of β. First, $h_0(t)$ can be allowed to vary in specified subsets of the data so that separate proportional hazards models are estimated for each sub–sample. This is achieved by dividing the sample into r strata and using $h_{0j}(t)$ as the baseline function (where j = 1,..., r) and then estimating the hazard function, $\hat{h}_j(t;\mathbf{x})$, for each strata. This generalization is particular useful for identifying the effects of covariates which do not appear to be multiplicative, since they can be used to define strata (Tuma et al., 1979). Second, Cox's model can incorporate time–varying covariates, in other words, it can allow elements of $\mathbf{x}$ to depend on time itself.

Kalbfleisch and Prentice (1980) distinguish between external and internal time dependent (ie. time–varying) covariates. External time dependent covariates are variables which are not influenced by duration but they may affect duration, such as the environmental influences outlined in Section 2.1.2. Internal time dependent covariates, on the other hand, are the outputs of the stochastic process generated by the individual (including the factors discussed in Section 2.1.1), implying that $\mathbf{x}(t)$ contains information about previous history. PLE can be used to estimate models with time–varying covariates (see Kalbfleisch & Prentice, 1980: Section 5.5) but the computer algorithms needed for derivation can be complex. Difficulties arise when the 'time until event occurrence' is measured more precisely than the interval at which explanatory variables are measured (Allison, 1984; Flinn & Heckman, 1982; Tuma et al., 1979). For example, if car ownership is intermittently measured, say every three months, during which time an individual may or may not have a car, whilst shopping events are recorded every time a trip is made, the problem becomes one of not knowing the exact time when the individuals car ownership status changed.

In discussion of both the parametric and partially parametric models it has been assumed that heterogeneity is fully specified by the included covariates (being time–varying or time–invariant). However, where omitted or unobserved heterogeneity exists it may be argued that a term to represent these omitted/unobserved sources of heterogeneity also needs to be included in event history models (Davies & Pickles, 1987; Dunn & Wrigley, 1985; Elbers & Ridder, 1982; Flinn & Heckman, 1982; Hannan, 1984; Reader, 1988; Winship, 1986; Wrigley, 1986). If unobserved heterogeneity is influencing the hazard rate and if such factors are ignored, negative duration dependence may be identified, a result which would be spurious and result in biased parameter estimates (Blossfeld et al., 1989; Heckman & Singer, 1982; Kalbfleisch & Prentice, 1980; Kiefer, 1988). Including a term to represent unobserved sources of heterogeneity into Cox's model (equation (2.5.36)) may look something like:

$$\hat{h}(t;\mathbf{x};\xi) = h_0(t) \exp\,(\beta;\mathbf{x};\xi), \tag{2.5.41}$$

where ξ represents the unobserved component of heterogeneity. The term ξ may take on a specified distributional form but parameter estimates may be severely affected if this distribution is misspecified (Heckman & Singer, 1982; Trussell and Richards, 1985). Alternatively, if repeat observations exist for individuals the unobserved heterogeneity distribution can be represented nonparametrically (see Heckman & Singer, 1982; Reader, 1988).

2.5.7 A Fully Generalized Continuous–Time Event History Model

Heckman (1981a) presents an integrated, generalized continuous–time event history model which includes all three sources of behavioural variation (ie. population heterogeneity, nonstationarity and state dependence). In Heckman's (1981a) model an event is postulated to occur at time t, for individual i, when a continuous latent random variable, $\hat{Y}(i,t)$ crosses a threshold (which is assumed to be zero). $\hat{Y}(i,t)$ is assumed to be a linear function of exogenous variables and is essentially a latent variable of utility, equivalent to the latent variable of lagged Markov models (Section 2.4.4). The model is defined as:

$$\hat{Y}(i,t) = X(i,t)\beta + \sum_{j=1}^{\infty} \gamma(t-j,t)d(i,t-j) + \sum_{j=1}^{\infty} \lambda(j,t-j) \prod_{q=1}^{j} d(i,t-q) + G(L)d(i,t) + e(i,t)\ , \tag{2.5.42}$$

where $\hat{Y}(i,t)$ is a binary, 1 or 0, variable, i =1,...,I; t=1,...,T. An event occurs (ie. $\hat{Y}(i,t) \geq 0$) when the a dummy variable, d(i,t), equals one and when d(i,t) equals zero an event does not occur. This event occurrence (ie. $\hat{Y}(i,t) \geq 0$ iff. d(i,t) = 1), is dependent on five terms. The first term in equation (2.5.42) accounts for the effects of exogenous variation on individual i at time t and in principle, these parameters may be dependent on time. The second term accounts for the effects of the entire past history on current choice in a finite Markov model. The third term accounts for the cumulative effects on the most recent time spent in a state, which generates a renewal process and would include inventory effects. The fourth term accounts for habit persistence in a latent Markov context. The fifth terms is an error variable which represents all other individual sources of variation not accounted for by the other four terms.

Heckman's (1981a) general model considers only dichotomous choice situations but it is flexible in that it can generate a variety of different models, including Polya, Markov and renewal models, (see Heckman, 1981a) which are applicable in studies of consumer purchasing behaviour (Timmermans & Borgers, 1989). Furthermore, time–varying exogenous variables can be incorporated in the first term of Heckman's model and unobserved, 'spurious' state dependence can be included in the fifth term. However, estimates from Heckman's (1981a) model are only practicable when the model is severely constrained given the data considerations and computational restrictions (Davies & Pickles, 1987). Consequently, Heckman's model presently is a useful theoretical construct rather than being a mathematically operational model and represents the type of fully generalized dynamic consumer behaviour models to which other continuous–time models should strive.

2.6 Conclusions

This chapter sought to convey how the substantive interpretation of the components of dynamic consumer shopping behaviour have been examined in the consumer purchasing literature and to review the progress towards generalized models of consumer purchasing behaviour. Initially, it was important to describe the factors which influence consumer decision–making and to conceptualize how these factors are considered in a modelling context. From this discussion it can be concluded that why an individual makes a particular purchasing decision is a complex problem. Consumer purchasing decisions are seldom clear–cut in reality, more often than not tradeoffs occur, weighing the advantages and disadvantages associated with making a particular choice. Observation of consumer behaviour indicates *what* purchases are made, not *why*. It is the job of the analyst to decipher behaviour patterns from empirical observation in order to determine the factors which influence decision–making behaviour. Models of consumer purchasing behaviour attempt to describe the decision–making process by making simplifying assumptions regarding the underlying behavioural process generating observed buying behaviour. Therefore, model predictions are only as useful as the behavioural assumptions made in the theoretical framework and can, at best, only provide approximation of actual decision–making behaviour. The usefulness of a particular modelling approach thus resides in developing models which accurately reflect observed behaviour, which is achieved by incorporating factors influencing consumer decisions which observations show to be important.

The Niscosia, EKB and Howard and Sheth models discussed in Section 2.1 all make simplifying assumptions concerning the relationship between an individual's purchase response and the factors which govern the decision. Of the three models, Niscosia's (1966) model is the most restrictive, assuming that effective messages from the firm always result in a positive response by the consumer (ie. a purchase). Engel, Kollat and Blackwell (1986) relax this 'necessarily positive response' assumption and also incorporate both external and internal factors as mechanisms for initiating the decision–making process. Howard and Sheth's (1968) model is the most generalized of the three in that it is formulated to specifically examine repeat purchasing behaviour and thus it explicitly considers time dependencies in the behavioural process. These time dependencies are assumed to be a function of the problem–solving task at hand and are influenced by exogenous variables which incorporate constraints on decision behaviour. In general, conceptual modelling approaches to consumer purchasing behaviour focus on specifying the underlying mechanisms involved in purchasing decisions and they provide deterministic evaluation of individual decision processes. These models are inherently dynamic, explicitly considering past history through learning and experience. However, these integrated–comprehensive models do not lend themselves to testing and thus simply provide theoretical frameworks upon which operational models may be based.

Empirical evaluation of consumer purchasing behaviour is a crucial part of any marketing or retailing strategy and hence the remainder of the discussion focused on developments in mathematically operational models of consumer purchasing behaviour. Since this thesis concerns time dependencies in consumer shopping behaviour, different modelling approaches were described that focus on the temporal and/or spatial aspects of discrete–choice behaviour.

Aggregate models are conventionally based on cross–sectional data and typically examine behaviour at a point in time. Aggregate predictions are thus governed by the specific conditions prevailing at the time of the empirical survey. Aggregate model formulations reflect a steady state in assuming that the past history of the behavioural process is independent of current choice. Given the increasing need for consumer behaviour information at the individual level, aggregate modelling approaches are becoming increasingly inappropriate to consumer purchasing analysis.

From the discussion of the aggregate approaches of Central Place Theory (CPT) and Spatial Interaction Models (SIMs) it is apparent that both ignore time dependencies and yet they have provided theoretical frameworks for much of the spatial behaviour literature. Central Place Theory is frequently criticized for possessing restrictive, unrealistic behavioural assumptions. However, the notion of a spatial retail hierarchy has proven to be a useful indicator of the degree to which behavioural realities deviate from CPT predictions of spatial patterns. Unlike CPT, SIMs provide probabilistic predictions of store choice. SIMs are flexible and have the potential to examine different types of shopping trips and individual shopping patterns. However, these models are not formulated at the level of the individual process.

Trip–chaining analysis is essentially a framework for analyzing spatial decision patterns rather than presenting a particular mathematical model of the behavioural process per se. Trip–chaining studies were reviewed because they are often based on longitudinal panel data and therefore have the potential to explicitly account for temporal changes in empirical shopping patterns. Trip chaining studies have employed a wide range of models, ranging from simple statistical analysis to complex integrations of a discrete–choice model operating as a semi–Markov process (Lerman 1979). The space–time budget approach may provide a general framework for analyzing store choice within spatial and temporal constraints, but the lack of a coherent approach within this field limits applications to essentially descriptive analysis. Although the space–time budget approach is conceptually appealing, a broader modelling framework is needed which addresses the complexity of spatial decisions if insight into observed behaviour is to be gained.

It is apparent from the discussion of purchase incidence modelling approaches that despite the wide range of application of these 'distributional–based' models to both aspatial and spatial behaviour, the simple behavioural assumptions underlying these models are incongruent with empirical observation. Most notably, these models have typically assumed temporal independence between purchases. This implies the highly unlikely scenario that the most likely time to visit a store is immediately following the last visit, in other words, inter–purchase times follow an exponential distribution. Davies and Pickles (1987) provide strong argument that inventory effects are not simply a theoretical notion but are a behavioural reality which are endogenous to the purchasing process. Also, whilst attempts to disaggregate purchase incidence models by incorporating population heterogeneity is an important step toward developing generalized applied models of consumer behaviour, attempts to incorporate time dependence into inter–purchase probabilities have not been as numerous nor as successful. With the exception of Davies and Pickles (1987), such attempts have involved seemingly arbitrary specification of an alternative parametric form to represent duration dependence, replacing the exponential with more regular distributions. It is apparent that current behavioural theories do not provide sufficient argument for one parametric form over another to represent the 'time until event occurrence'. Given this, it is most likely that insight will only be gained from empirical investigations as to the form of duration dependence occurring in observed purchasing patterns.

Random utility maximization provides an operational framework for considering the tradeoffs associated with individual decisions. These tradeoffs are expressed in utility values, the validity of which depends on the ability of the model to represent both the systematic and random components of the decision–making/choice process. The majority of discrete–choice model applications, restricted in the past by access only to cross–sectional data, have sought to model aggregate behaviour rather than identify the process and variation inherent in behaviour at the individual level. In fact, the universal choice set assumption of discrete–choice which underlies the IIA problem of MNL models is essentially a problem of defining a choice set that is relevant to a population/locality, and is conceptually equivalent to the variance discrepancy of aggregate purchase incidence models. In order to fully understand individual (spatial) choice behaviour the causal link between a decision–maker and her/his choice alternative(s) needs to be explicitly identified, a link which is frequently governed by past choice decisions and by learning about 'new' alternatives. Dynamic discrete–choice models are needed in order to explicitly consider the interrelationships among choices, population heterogeneity, state dependence and learning effects. Thus with few exceptions (Tardiff, 1980; Manski, 1981), emphasis of discrete–choice model applications has been on cross–sectional data even if the choice process governing behaviour is inherently dynamic.

Furthermore, with the notable exception of Fotheringham (1989; 1988), applied discrete–choice models have concentrated on aspatial behaviour with little regard for the transferability of these models to spatial choice situations. The most advanced discrete–choice models to date are generalized dynamic models which identify the various factors governing temporally correlated behaviour decisions. Such models are internally dynamic, accounting for endogenous determinants of behaviour (ie. structural state dependence) and externally dynamic, accounting for changes in exogenous determinants of behaviour (ie. heterogeneity). The 'Master–equation approach' provides a useful typology for stochastic modelling, incorporating the influence of different sources of behavioural variation in one general discrete–choice dynamic model (see Haag, 1989; Haag & Weildlich, 1988 for description of the 'Master–equation approach). However, a bottleneck exists regarding the application of methodologies of dynamic discrete–choice models in empirical research due, in part, to the statistical complexity and data requirements of these models, but also because of the lack of attention to complex behavioural theories supporting or underlying the mathematical/statistical methodologies.

In their basic forms, both aggregate and discrete–choice models inherently fail to consider the influence of time dependence in behavioural processes. Neglecting the endogenous determinants in consumer purchasing models inevitably leads to a statistical association between the determinants of behaviour included in the analysis (ie. covariates) and those excluded from the analysis (ie. the error term). Formally this problem reduces to that of a violation of the independence assumption between the exogenous variables and the error term. The consequences of such violation precludes consistent parameter estimates, necessary for statistical inference.

Section 2.4 described the way in which endogenous determinants of consumer behaviour processes are examined in a mathematical modelling context. "Feedback"/adaptive–behaviour models explicitly consider learning and experience as endogenous to the probability that an individual will make a particular purchase choice. Evidence from loyalty studies indicate that shopping behaviour is indeed more regular than random. Explicit consideration of observed past purchasing behaviour on current probability is addressed in the Linear Learning Model (LLM). It is interesting to note that the LLM is surpassed in popularity by the simple homogeneous Markov model, largely due to the basic simplicity of the Markov model as compared to the complex feedback dependency of the LLM, leaving the latter model as somewhat of an enigma, even among professional researchers (Massy et al., 1970). The simple Markov model incorporates assumptions about the influence of purchase–event feedback on consumer choice behaviour but does not inherently consider the dynamic nature behaviour decisions. In effect, the simple Markov model is an extension of the stationary homogeneous Bernoulli model (Massy et al., 1970). Markovian processes provide a rudimentary framework for considering adaptive consumer choice behaviour, inherently addressing previous purchases, to varying degrees, in the specification of transition rates. The rigorous assumptions of simple–Markov models, notably the independence of path assumption, limit applicability, but generalized Markov models have developed which include heterogeneity and intertemporal time dependence and have proven useful in studies of social phenomena. In their basic forms, however, these models assume that transitions between states occur at specifically defined points in time thus these models examine a behavioural process which is subdivided into discrete sets of observational units.

In the context of consumer shopping, the underlying behavioural process operates in continuous–time (as attitudes, preferences and consumption behaviour perpetually change) but manifests itself in a series of discrete events (ie. the generation of a shopping trip). It is argued that continuous–time methods are more 'natural' because even if events operated at discrete intervals of time, there is no a priori reason to assume that they would correspond to annual, monthly or weekly events. This argument partly reflects limitations found with temporally aggregate panel data previously available, but also indicates the relative lack of attention given to time dependencies in consumer behaviour modelling approaches. Even if empirical conditions are predominantly stable, longitudinal event history data is more general than cross–sectional data since cross–sectional data can be reconstructed from longitudinal histories. Furthermore, longitudinal data is more informative in empirical applications because only through longitudinal data can it be demonstrated whether stable conditions really do exist over time.

Continuous–time methods are derived from longitudinal event history data. Inherently, these models consider the role of duration dependence, as reflected in the use of hazard rates and consequently, these models are ideal for empirical investigation of dynamic shopping behaviour. Parametric continuous–time regression models using such distributions as the Weibull, and log–logistic may involve stronger distributional assumptions than are appropriate to a particular study. If primary interest resides in estimating the influence of observed covariates on hazard rates, partially parametric approaches such as Cox's model may be employed. The objective of partially parametric methods is to develop efficient inference procedures for the estimation of covariate parameters. If event data is discrete (for example, due to imprecise measurement) continuous–time models can generate discrete–time analogues, achieved by grouping the time axis into temporally discrete intervals (see Allison, 1984; Blossfeld et al., 1989; Kalbfleisch & Prentice, 1980 for the discrete–time derivations of continuous–time models).

The field of consumer behaviour modelling is at a pivotal stage in its development. The combination of a methodological trend toward dynamic models of behaviour and the trend toward the collection of longitudinal information using scanner panels will revolutionize the way in which consumer purchasing behaviour is analyzed. Within the field of consumer behaviour modelling we can look forward to developing fully generalized models such as those of Heckman (1981a) which in the absence of suitable data, have been regarded as interesting theoretical constructs. With the exception of Davies and Pickles (1987) study, recent applications of disaggregate event history data to consumer behaviour studies involving store choice have tended to emphasize the importance of incorporating population heterogeneity into consumer behaviour models. Consequently, this research seeks to redress the balance by concentrating on the endogenous influence of time dependencies in consumer shopping behaviour. The focus of this analysis is on duration dependence so that the distributional form of duration dependence occurring in empirically observed spatial behaviour can be assessed. A continuous–time event history modelling approach is adopted due to its obvious advantages for empirical investigations of dynamic behavioural processes.

CHAPTER THREE

RESEARCH METHODOLOGY

Before describing the data and the methodological procedures used in this analysis, it is useful to recall the factors which need to be considered in a generalized model of store switching behaviour. In such a model the factors influencing the probabilities of a consumer choosing a particular store can be usefully divided into static and dynamic components (Reader, 1988). The static components refer to time–invariant exogenous variables which relate to a particular store alternative or to a consumer. Variables which relate to store choice and which are liable to be important to decision–making may include such attributes as store size, cleanliness, availability of parking space and quality of service. Variables which relate to the consumer and which are likely to be important include car availability, family structure, freezer ownership, income status, accessibility to stores, etc. Both choice–based and consumer–based exogenous variables (covariates) can be observed or unobserved (see Section 2.1.6).

Dynamic components of consumer choice models cause the probability of choosing a particular store alternative to vary with time. Time–varying exogenous variables are summarized in nonstationarity (Section 2.1.6) and can be decomposed into two types of factors. The first of these includes changes in the purchasing environment, such as changes in the choice alternatives, which would affect all individuals the same way. These may also be observed or unobserved depending on the level of information collected. It is, for example, easier to observe changes in store opening hours than changes in product availability. The second type of factor deals with changes that may be specific to a particular consumer and which affect the rate of the purchasing process. In the case of shopping behaviour, fluctuations in personal propensity to consume per se, would be an example of a nonstationarity influence. Empirical evidence indicates that consumer behaviour is, indeed, prone to nonstationarity elements (Broom & Wrigley, 1983; Guy et al., 1983; Uncles, 1985) and one method of handling such elements, if they are consistent and have simple form, is to use 'operational time' for model specification. 'Operational time' refers to manipulation of the temporal scale used to measure the process wherein the scale reflects changes in the rate of the process. Essentially, this method has the effect of making nonstationary processes appear stationary (Davies & Pickles, 1987; Davies et al., 1982; Goodhardt et al., 1984; Massy et al., 1970; Tuma & Hannan, 1984). However, it can be argued that in a short–run behavioural process like shopping, an assumption of stationarity conditions is more valid than in longer–term behavioural processes such as job or residential migration. Consequently, mathematical models of consumer behaviour have often assumed stationarity conditions for analytical convenience and bearing on the the fact that the data used in this research relates to a short–term process (ie. an observation period of 24 weeks) the stationarity assumption approach was adopted in this study.

In addition to nonstationarity effects, there are a number of endogenous factors which constitute dynamic components of consumer behaviour, some of which are the focus of this research. In the terminology of Section 2.1.6, these endogenous factors are state dependence effects and can conveniently be considered as operating though a household's grocery inventory. At any point in time, a household will have a particular level of grocery products which can be assessed relative to a perceived level of inventory needed to meet anticipated consumption. The probability of a shopping trip to a retail outlet depends on the relationship between actual inventory held and perceived inventory need. The level of actual inventory held will most certainly depend on the time elapsed since previous shopping trips. Moreover, if we assume that different grocery store types tend to be used for different levels of inventory replenishment, then both the *state* and *timing* of previous trips is seen to be important. Evidence from store choice and store loyalty studies indicates that such an assumption is a reasonable one (Carman, 1970; Davies & Pickles, 1987; Reader, 1988; Uncles, 1988; Wrigley & Dunn, 1984c; 1984d). This assumption implies that if the perceived difference between actual inventory held and anticipated consumption need increases, so does the probability of a trip to a larger retail outlet, such as a superstore. On the other hand, if this perceived difference is small and relates to only a small number of particular products, the probability of a trip to a local or *convenience* store for 'filler' or 'topping–up' purchases is likely to be high. From this discussion it is easy to imagine how the probability of choosing to shop at a particular type of retail outlet may depend on both the type of retail outlet visited in the preceding trip and the time elapsed since that trip. In the terminology of Chapter Two this corresponds to both Markov and duration dependencies operating in the behavioural process (ie. a semi–Markov process) and which forms the basis of the analysis in this thesis. However it should be noted that a truly comprehensive approach to analyzing consumer behaviour would extend consideration to those endogenous variables representing inventory effects of shopping trips n orders removed from the most recent trip (ie. an *n–order* semi–Markov process). Indeed, if we are to consider the true influence of learning and experience in the behavioural process then, theoretically, we must extend the model to examine the entire history of store visits.

3.1 The Cardiff Consumer Panel

The longitudinal data used in this study is taken from the ESRC funded Cardiff Consumer Panel (see Guy et al., 1983 for details). The Cardiff Consumer Panel is particularly well suited to this analysis as it contains purchasing records for each and every grocery store visit made by panel households over a 24 week period (January to July, 1982). The Cardiff Consumer Panel was collected by manual diary methods but its size, level of temporal disaggregation, spatial coverage and purchasing information detail is comparable to modern consumer scanner panel data sets. The Cardiff Consumer Panel records information on the timing and location of each store visit as well as the characteristics of the shopping trip such as mode of travel, the origin and destination of each trip and whether or not a store visit was a single stop or a multipurpose trip. In addition, records contain information on the number, types of products bought and the total expenditure of the shop visit. Furthermore, data from two questionnaires provide information on the socio–demographic characteristics of each household, including length of residence, household composition and working status. Figure A.1 of Appendix A presents an example diary page which a panellist would complete each time a grocery store was visited. The questionnaires completed by panel members at the beginning of the study period (A.2) and at the end of the survey (A.3) are also given in Appendix A.

Panellists were recruited from eight spatially distinct study areas in Cardiff, Wales. These eight areas were chosen using a stratified, multi–stage sampling scheme. Fifty Enumeration Districts, as classified in the 1971 Census, were stratified according to three binary indicator variables, (1) *accessibility to local shops*, divided into 'good' or 'poor' on the basis of more than or less than eight food shops within a quarter mile of the centroid of the enumeration district; (2) *accessibility to district centres*, categorized as 'good' or 'poor' on the basis of a district centre located more than or less than half a mile from the centroid of the enumeration district; and (3) *potential mobility*, as 'good' or 'poor' on the basis of the district car ownership rate being above or below 50%. Within each stratum enumeration districts were then selected subject to two considerations: (i) that the selected areas had to be east of the River Taff and north of the city centre, and (ii) if a sufficient sample of households could not be recruited from the selected areas, contiguous enumeration districts which shared similar characteristics could be included to meet requirements (Guy et al., 1983). The locations of the resulting eight study areas chosen for the Cardiff panel are illustrated in Figure 3.1.1 (page 145). By name, these study areas are Rhiwbina, Llanederyn, Llanrumney, Rumney, Heath, Whitchurch, Cathays and Roath and the characteristics of the strata defining each of these study areas is listed in Table 3.1.1 (page 146). Households within each area were then sampled from the 1981–1982 city electoral role. Given that the study areas were chosen on the basis of 1971 data and the panellists were sampled using early 1980's data, great care was exercised to ensure that the two sampling frames matched each other (see Guy et al., 1983:13 for details). The number of households recruited in each of the eight study areas who remained on the panel for the entire study period is also listed in Table 3.1.1.

Each retail outlet used by panellists was allocated a unique numerical code. These shop codes contain information on the location of the store, its function, its organization and a unique digit to distinguish individual premises. From the shop code information a distinction can be made between district and 'local' centres. The location of district centres, labelled 2 through 9 in Figure 3.1.1 are as defined in the South Glamorgan 1977 Structure Plan. The designated district centres indicated in Figure 3.1.1 correspond to areas which constitute district centres for the purpose of this study and comprise four additional locations. Cardiff's city centre is treated as a district centre because it contains a large number of grocery outlets including a superstore (ie. a store with more than 2000 square meters of net sales area), two

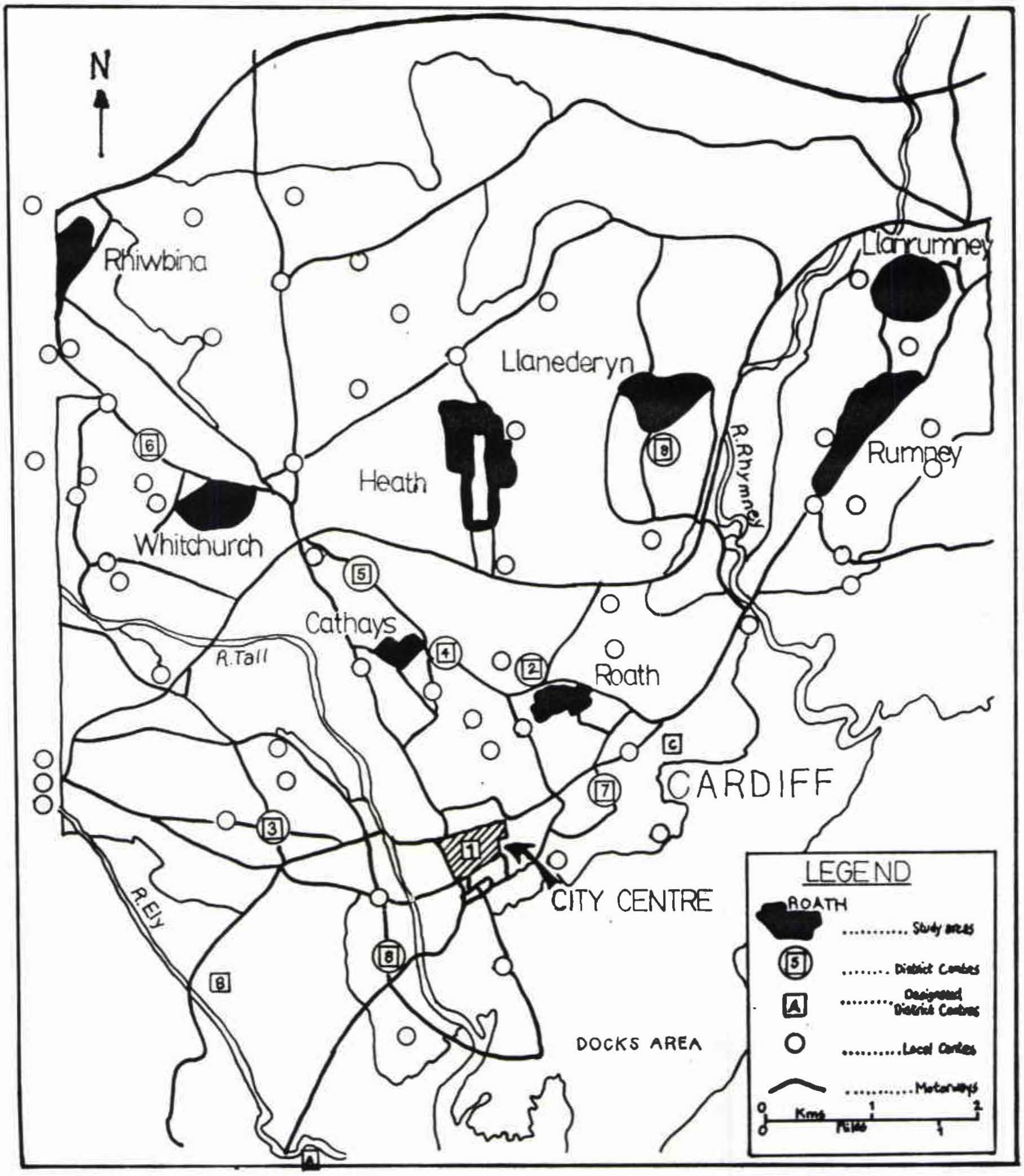


Figure 3.1.1: Location of study areas and shopping centres in Cardiff, Wales

(based on: Guy et al., 1983:24)

Table 3.1.1: Characteristics of the Cardiff Consumer Panel study areas (based on: Guy et al., 1983:25)

Study Area	Accessibility to Local Centres*	Accessibilty to District Centres**	Potential Mobility***	Number of Panellists (%)
Rhiwbina	Poor	Poor	Poor	88 (19.5%)
Llanederyn	Poor	Good	Good	54 (12.0%)
Llanrumney	Good	Poor	Poor	66 (14.6%)
Rumney	Poor	Poor	Poor	60 (13.3%)
Heath	Poor	Poor	Good	39 (8.6%)
Whitchurch	Good	Poor	Good	44 (9.8%)
Cathays	Good	Good	Good	73 (16.2%)
Roath	Good	Good	Poor	27 (6.0%)

* 'Good' or 'Poor' on the basis of more or less than eight food shop within a quarter-mile of the centroid of the enumeration district

** 'Good' or 'Poor' on the basis of a district centre located more or less than half a mile from the centroid of the enumeration district

*** 'Good' or 'Poor' on the basis of district car ownership rate above or below 0.5 cars per household large food markets, the city's fish market and numerous other stores which sell grocery products. Also, Leo's superstore on Penarth Road (labelled A in Figure 3.1.1), Dodge City on Hadfield Road (B) and Leo's superstore on Moorland Street (C) are designated as district centres, given the heavy concentration of grocery retail selling floorspace they represent as superstores. 'Local' centres refer to an 'all other store' category, although it should be emphasized that the choice of this term refers more to a functional definition (size) rather than a geographical one. In other words, trips made to local centres reflect all trips other than those which were made to the designated district centres, so that it is possible that local store trips may be to stores which are quite distant from the panellist's residence, nevertheless, many such local store trips would indeed be to small stores in close proximity to the panellist's home. Although the definitions of centres is a functional one, based on size, the location of the district centres relative to the study areas means that a geographical distinction is essentially retained. The degree of this geographical element obviously varies between study areas.

Within the purchasing data itself, one problem faced in this study was that information on the number of units of an item purchased on any one particular occasion was not collected. This limitation of the data set means that those individuals who bought multiple units of a product on a single visit potentially decreased the time until another store visit for purchases of that product was made. Thus diary records only indicate whether or not a particular product was purchased on a specific store visit and not how much was purchased on any one trip.

The Cardiff Consumer Panel of 'continuous reporters' contains information on 451 households, over 80,000 store visits to approximately 1,000 different retail outlets. 'Continuous reporters', refer to individuals who were away from their homes no more than 32 days out of the 24 weeks and with no more than 15 consecutive days away at one time. The 24 week survey period extended over

Easter holidays, bank holidays and the beginning of summer holidays and, consequently, minor absences of 'continuous reporters' were regarded as days on which nothing was purchased (Guy et al., 1983). Of the 'continuous reporters', 82 percent had no absences of more than seven days while 41 percent were not away from their household for a single day during the study period. 'Continuous reporters' also satisfactorily completed the manual diaries and responded to both the initial and final questionnaires. Figure A.3 and Table A.1 of Appendix A summarize the attitudes and characteristics of the 451 Cardiff 'continuous reporters', respectively, who are hereafter simply referred to as panellists or households.

The majority of the panellists are women (93.8%), 76.5% of which classifed themselves as wives of the head of the household. Approximately, 86% of the panel was between the ages of 25 to 64 and about 54% were not working during the study period. Over half of the respondents had been living in their 1982 residence for over ten years, implying that many of the panel members would have been familiar with the available store alternatives. The *attitudinal questionnaire* information revealed that panellists were equally divided between those who *preferred* to shop only at one store (about 49%) as opposed to those who *preferred* multi–store shopping (approximately 49%). Also, while over 77% of panellists agreed that chain stores and supermarkets made for better all round grocery shopping, 62.7% felt that the convenience of local shops was worth the extra it may cost. Furthermore, over half of the panellists felt that some type of difference exists between alternative retail outlets which, in turn, implies that these individuals made a conscious distinction between different types of shops and therefore actively selected their choice of store.

3.2 The Study Data Set

Of the 451 Cardiff households, 424 households are examined in this study. The common factor these 424 households share is that they all purchased the product category of 'baked beans' (product field 21 in Figure A.1, Appendix A) at least once during the 24 week study period. This type of product approach is commonly found in the store switching literature (Aaker & Jones, 1971; Carman, 1970; Cunningham, 1961; 1956; Davies & Pickles, 1987; Dunn et al., 1983; Ehrenberg, 1988; Gollins, 1989; Kau & Ehrenberg, 1988; Rao, 1969; Wrigley & Dunn, 1988; 1984a; 1984b; 1984c; 1985d; Wrigley, 1980) and is a standard method used to analyze purchasing behaviour. Historically, data on numerous products was unavailable, partly reflecting the research emphasis on products as opposed to stores. Although store based data on numerous products for all shopping trips are available to this analysis the single product approach is maintained, partly for consistency, but, more practically, because this approach acts as a sampling frame of all shopping trips.

Several criteria were imposed which led to the selection of baked beans as the product to be investigated from all those available in the Cardiff survey data. Firstly, it was recognized that analysis of store switching behaviour between the spatially distinct centres required that the product be widely available in different outlets throughout the Cardiff area. Baked beans is essentially a food staple in the British diet and, as such, is offered for sale throughout local and district centres in Cardiff. Secondly, to avoid problems associated with nonstationarity in the availability of foods which, in turn, could impose nonstationarity in purchasing rates, seasonal goods such as ice cream, fresh fruit and fresh vegetables were not considered. Thirdly, the chosen product had to be frequently demanded by a majority of Cardiff consumers, so that as representative a sample as possible is preserved. These requirements are satisfied by the product category of baked beans.

Fourthly, heavily purchased products, defined here as those with more than 25 purchases in 24 weeks, were excluded because, by definition, the amount of variation in purchasing times is limited and thus would restrict the ability to analyze temporal influences. Figure 3.2.1 (page 151) illustrates the distribution of the number of buying occasions across the buying consumers for the product category baked beans. Only 6.4% of the panellists do not buy baked beans at all and over 83% of the buying population purchase baked beans less than 25 times over the 24 weeks. Details on the number of buyers for the other food items examined in the Cardiff Panel are given in Table A.2 of Appendix A. Baked beans also has a fairly even distribution of buying occasions across the buying population. From Figure 3.2.1 it is apparent that about 30% buy baked beans one to six times, 42% buy seven to seventeen times, and 26% buy 18 to 24 times over the study period. Only eight foodstuffs other than baked beans exhibit such an even distribution of buyers (see Table A.2, Appendix A). Also, previous studies, in particular those of Wrigley and Dunn (1984a; 1984b; 1984c; 1985d), have examined store choice behaviour focusing on baked beans purchases using the Cardiff Consumer Panel.

For the purposes of this study, a *purchase* occasion is defined as the purchase of the product category baked beans at a particular store. The data used in this thesis makes a distinction between two types of store visits, those made to stores located within district centres from those made to local centre stores. Recall that although the distinction between centres is largely a function of store size, the geographical distinction between these two types of stores is essentially retained. A *switch* is observed to occur when a panellist purchases the product category baked beans at a store type which is different to that at which the previous purchase of the product category occurred. At any particular time a panellist is treated as being in the *state* corresponding to the type of store last visited. Consequently, the *duration* between switches can be defined as the amount of time that a panellist is observed

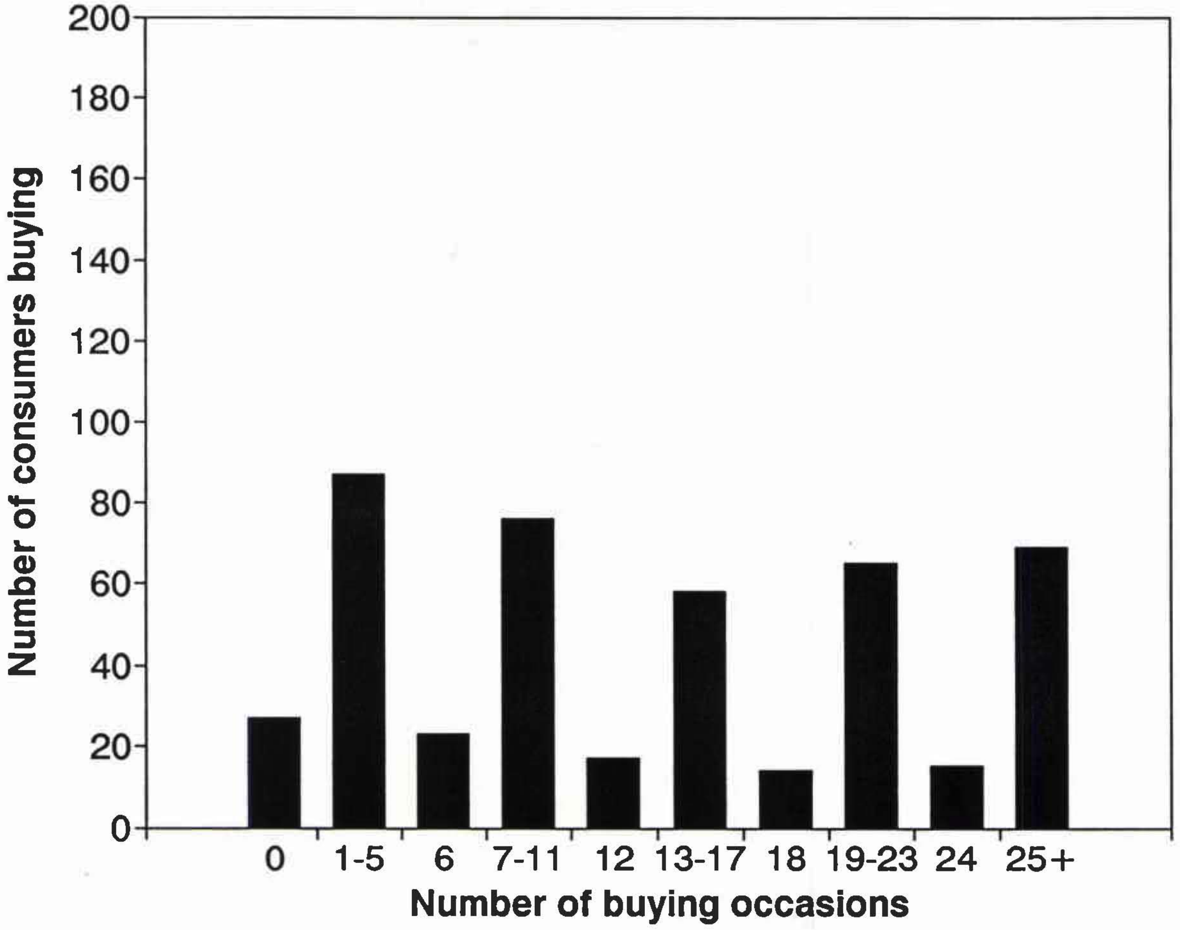


Figure 3.2.1: Distribution of consumer purchases of the product category baked beans

to stay *loyal* to a particular store type, ie. remains in a particular state. For example, if a panellist were to begin to purchase the product category baked beans at stores within different district centres on the fifth, tenth, and fifteenth day of the survey period and then was to purchase the product category at a local store on the eighteenth day, a switch would be recorded on the eighteenth day whilst a duration of thirteen days would be observed for the loyalty to district centre stores.

An example of the data used in this analysis is given in Table 3.2.1 (page 153). Each of the 1,195 observations in this data set represents a switch between shopping at different centres (ie. store types) by a household for the purchase of the product category baked beans. The observations record the characteristics of the *switch* including information on the panellist (as identified by a unique number), the actual date on which the product began to be purchased at one store type, (DAY PURCHASE), the actual date of the switch to purchasing at the other store type, (DAY SWITCH), and the actual types of stores involved (the START STATE and END STATE variables). The censoring variable, (CENSOR), of Table 3.2.1 accounts for the right censored data (Section 2.5.1) which occur in this longitudinal data set. In the context of this thesis, right–censored duration observations occur when a consumer continues to shop at either district or local centres from a particular day in the study period until the last day, ie. day 168. The duration variable, (DURATION), refers to the length of time (in days) that a panellist remains *loyal* to a particular store type. In other words, duration corresponds to the 'time until event occurrence' (Section 2.5.3) where an event is synonymous with a centre switch. It is possible that the degree of loyalty to a particular store type (as measured by duration) depends, at least in part, on the characteristics of the individual so that if different 'types' of individuals tend to shop at a particular centre then the buying patterns associated with district store shopping may differ from those associated with local store shopping. Recurrent visits to one type of

CONSUMER ID.	DAY PURCHASE	DAY SWITCH	START STATE	END STATE	CENSOR	DURATION	NIP	LOR	FFO	DFO	NCAR	USEC	LIC	AGE	MART	EMPLY	INC	YC	OC	HSZ	FREQ	ALS	ADS
1	5	19	1	0	1	14	1	6	0	1	1	1	0	3	1	1	6	1	1	4	4	0	0
1	19	26	0	1	1	7	0	6	0	1	1	1	0	3	1	1	6	1	1	4	4	0	0
1	26	31	1	0	1	5	0	6	0	1	1	1	0	3	1	1	6	1	1	4	4	0	0
1	31	34	0	1	1	3	1	6	0	1	1	1	0	3	1	1	6	1	1	4	4	0	0
1	34	67	1	0	1	33	4	6	0	1	1	1	0	3	1	1	6	1	1	4	4	0	0
1	67	68	0	1	1	1	0	6	0	1	1	1	0	3	1	1	6	1	1	4	4	0	0
1	68	71	1	0	1	3	0	6	0	1	1	1	0	3	1	1	6	1	1	4	4	0	0
1	71	75	0	1	1	4	0	6	0	1	1	1	0	3	1	1	6	1	1	4	4	0	0
1	75	80	1	0	1	5	0	6	0	1	1	1	0	3	1	1	6	1	1	4	4	0	0
1	80	83	0	1	1	3	0	6	0	1	1	1	0	3	1	1	6	1	1	4	4	0	0
1	83	121	1	0	1	38	4	6	0	1	1	1	0	3	1	1	6	1	1	4	4	0	0
1	21	124	0	1	1	3	0	6	0	1	1	1	0	3	1	1	6	1	1	4	4	0	0
1	24	143	1	0	1	19	2	6	0	1	1	1	0	3	1	1	6	1	1	4	4	0	0
1	43	145	0	1	1	2	0	6	0	1	1	1	0	3	1	1	6	1	1	4	4	0	0
1	45	168	1	1	0	23	3	6	0	1	1	1	0	3	1	1	6	1	1	4	4	0	0
2	4	168	1	1	0	164	23	7	0	0	1	1	0	5	1	0	5	0	0	2	6	0	0
3	11	30	1	0	1	19	1	6	0	1	2	2	1	3	1	0	7	0	1	6	3	0	0
3	30	33	0	1	1	3	0	6	0	1	2	2	1	3	1	0	7	0	1	6	3	0	0
3	33	50	1	0	1	17	1	6	0	1	2	2	1	3	1	0	7	0	1	6	3	0	0
3	50	53	0	1	1	3	0	6	0	1	2	2	1	3	1	0	7	0	1	6	3	0	0
3	53	68	1	0	1	15	0	6	0	1	2	2	1	3	1	0	7	0	1	6	3	0	0
3	68	74	0	1	1	6	1	6	0	1	2	2	1	3	1	0	7	0	1	6	3	0	0
3	74	89	1	0	1	15	0	6	0	1	2	2	1	3	1	0	7	0	1	6	3	0	0
3	89	96	0	1	1	7	0	6	0	1	2	2	1	3	1	0	7	0	1	6	3	0	0
3	96	136	1	0	1	40	1	6	0	1	2	2	1	3	1	0	7	0	1	6	3	0	0
3	36	143	0	1	1	7	0	6	0	1	2	2	1	3	1	0	7	0	1	6	3	0	0
3	43	153	1	0	1	10	0	6	0	1	2	2	1	3	1	0	7	0	1	6	3	0	0
3	53	160	0	1	1	7	0	6	0	1	2	2	1	3	1	0	7	0	1	6	3	0	0
3	60	168	1	1	0	8	1	6	0	1	2	2	1	3	1	0	7	0	1	6	3	0	0

Table 3.2.1: The first 29 observations examined in this study

centre is measured by the number of interpurchases (NIP) variable which reflects the number of repeat visits to a particular store type (district or local) that a consumer makes during this period (duration) of loyalty. This number of visits will affect household inventory levels and consequently will likely be an important influence on the duration between centre switches.

The distribution of the number of interpurchases which are observed over the 24 week study period is illustrated in Figure 3.2.2 (page 155). From the figure it is apparent that the number of interpurchases (NIP) made by households over the study period varies widely from 0 to 51. Approximately, 43% of the observed durations did not involve any interpurchases, ie. these durations represent a direct *switch* between centre types for purchases of the product category baked beans. The remaining 57% of the observations involve repeat visits to the same type of centre within a particular 'duration'. Approximately 13% of observations are for one interpurchase, which is roughly equal to the number of observations for 2 to 3, 4 to 7, and 8 to 21 interpurchases. Only 5% of the observations are for 22 to 51 interpurchases and it is likely that a great many of these observations come from individuals who are loyal to a particular type of centre for practically the entire study period.

From the research cited in Section 2.2.3, it is apparent that individuals tend to organize activities into trip chains so that the timing and destination for a particular store visit may be affected by the characteristics of the trip. The diary information includes data concerning the characteristics of the shopping trip, such as the person in the household who bought baked beans on a specific shopping trip, the mode of travel used to visit the centre and whether or not a multipurpose trip occurred. Although these factors are likely to be influencing the duration between store visits they are not examined in this research. The person in the household who bought baked beans would be of interest if this study was concerned, for

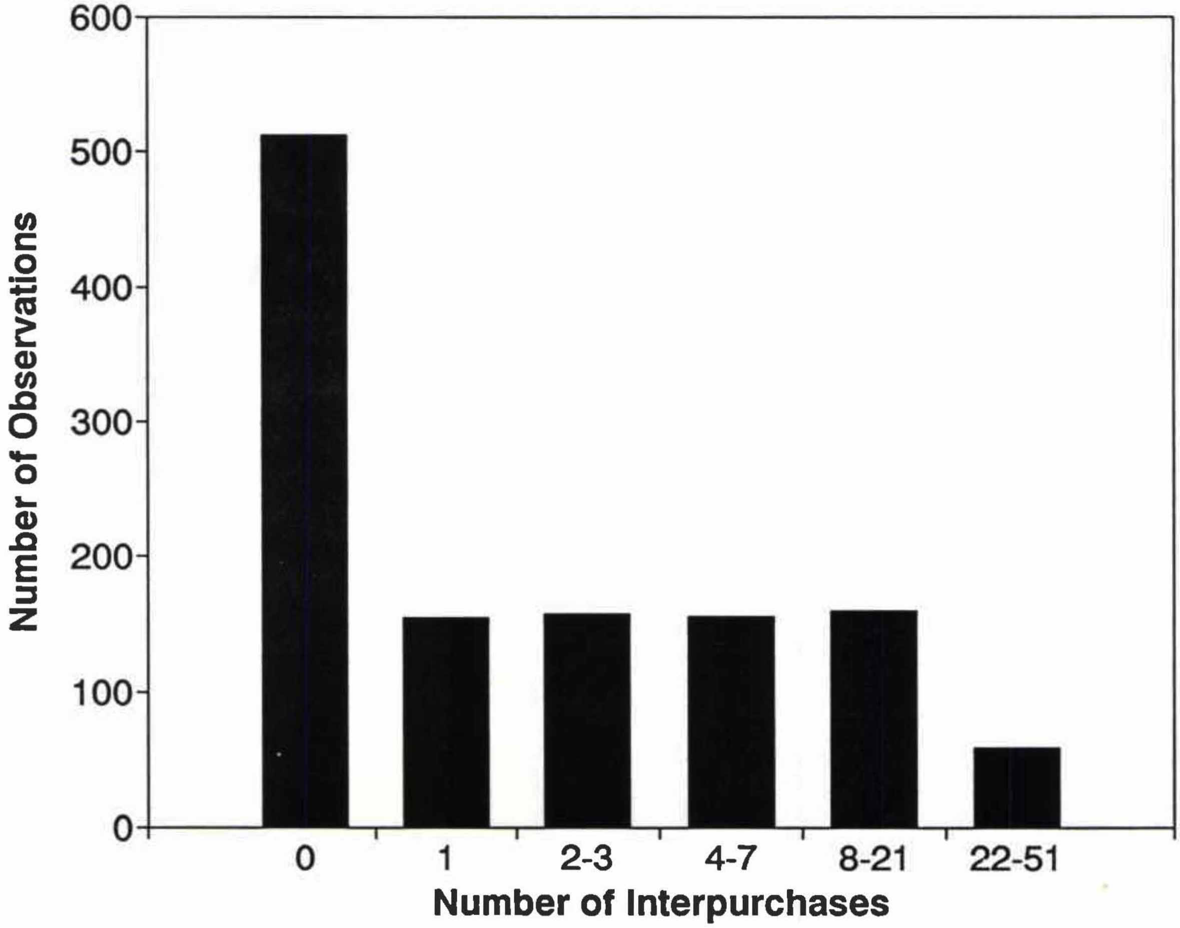


Figure 3.2.2: Distribution of the number of interpurchases (NIP) of the product category baked beans

example, with individual consumption rates or individual preferences toward specific brands, but here focus is simply on household inventory and shopping patterns of the product category baked beans. The characteristics of the shopping trip are difficult to include in this analysis because such factors would influence each individual's behaviour patterns differently and thus incorporating trip characteristics would require more detailed information than that provided by the Cardiff Consumer Panel. The difficulty arises in measuring the characteristics of a trip when they do not change at a time when the duration between store switches changes, the problem being the identification of which factors are affecting one particular store visit. Furthermore, other factors may influence the relationship between trip characteristics and the duration between store type switches which are beyond the scope of this study. Therefore, this research assumes that the duration between centre switches is influenced by the previous type of centre visited, the number of purchases made while a panellist remains *loyal* to a particular store type, inventory effects and the characteristics of the household.

Information on household characteristics is derived from the questionnaire data files of the Cardiff panel and account for measured sources of population heterogeneity which may influence household inventory levels. The specific factors which were examined in this study are given in Table 3.2.2 (page 157). A comparison is made between the distribution of household characteristics associated with the observations examined in this study and the distribution of household characteristics associated with individuals in the Cardiff Consumer Panel as a whole, in order to assess the relative differences. Most of these variables have been examined in previous studies that have used the Cardiff Consumer Panel data and, in general, have been found to be significant influences on probability estimates of consumer behaviour (Davies & Pickles, 1987; Dunn & Wrigley, 1983; Moore, 1989; Reader, 1988; Reader & Uncles, 1988; Uncles, 1987; Wrigley & Dunn, 1988; 1985d).

Table 3.2.2: Definition and number of observations of the household characteristic variables

Exogenous Variable	No. of Observations (%)	Cardiff Panel %	Code
Length of Residence (LOR):			
0 < 3 months	1 (0.1)	0.2	1
3 - 5 months	15 (1.3)	1.1	2
6 < 12 months	69 (5.8)	5.1	3
1 < 2 years	55 (4.6)	5.1	4
2 < 3 years	80 (6.7)	6.7	5
3 < 10 years	404 (33.8)	25.9	6
10 + years	564 (47.2)	55.2	7
unknown	7 (0.6)	0.7	9
Fridge with Freezer Owned (FFO):			
no	776 (64.9)	65.9	0
yes	416 (34.8)	33.5	1
unknown	3 (0.3)	0.7	2
Deep Freezer Owned (DFO):			
no	710 (59.4)	54.3	0
yes	478 (40.0)	45.2	1
unknown	7 (0.6)	0.4	2
No. of Cars (Vans) Owned (NCAR):			
none	337 (28.2)	30.2	0
one	633 (53.0)	53.4	1
two or more	225 (18.8)	16.2	2
Use of Car for Shopping (USEC):			
never	448 (37.5)	36.8	0
sometimes	394 (33.0)	33.5	1
all the time	353 (29.5)	29.7	2
Drivers Licence Owned (LIC):			
no	804 (67.3)	64.1	0
yes	391 (32.7)	35.9	1
Age (AGE):			
16 - 24 years	56 (4.7)	3.8	1
25 - 34 years	459 (38.4)	29.7	2
35 - 44 years	228 (19.1)	18.2	3
45 - 54 years	245 (20.5)	19.7	4
55 - 64 years	154 (12.9)	18.2	5
65 + years	53 (4.4)	10.4	6
Marital Status (MART):			
single (divorced, widowed)	169 (14.1)	19.1	0
married	1026 (85.9)	80.1	1
Employment Status (EMPLY)			
not employed	647 (54.1)	54.5	0
employed part-time/student	355 (29.7)	30.2	1
employed full-time	193 (16.2)	15.3	2

Table 3.2.2 continued... Exogenous Variable	No. of Observations (%)	Cardiff Panel %	Code
Household Income (INC):			
£0 - 1999	11 (0.9)	2.7	1
£2000 - 4999	312 (26.1)	24.8	2
£5000 - 6999	208 (17.4)	12.9	3
£7000 - 9999	141 (11.8)	14.2	4
£10000 - 14999	110 (9.2)	9.8	5
£15000 +	40 (3.3)	3.1	6
unknown	373 (31.2)	32.6	9
No. of Children: 0 - 4 years (YC):			
none	915 (76.6)	80.7	0
one or more	280 (23.4)	19.3	1
No. of Children: 5 - 15 years (OC):			
none	489 (40.9)	55.2	0
one or more	706 (59.1)	44.8	1
Household Size (HSZ):			
1 person	43 (3.6)	7.3	1
2 person	185 (15.5)	25.1	2
3 person	229 (19.2)	20.0	3
4 person	357 (29.9)	27.5	4
5 person	204 (17.1)	12.9	5
6 person	155 (13.0)	6.4	6
7 person	22 (1.8)	0.9	7
Frequency of Weekly Shopping (FREQ):			
irregular	72 (6.0)	4.9	0
once	251 (21.0)	23.2	1
twice	194 (16.2)	19.1	2
three times	191 (16.0)	16.0	3
four times	162 (13.6)	13.1	4
five times	39 (3.3)	3.3	5
six or more times	286 (23.9)	20.4	6
Accessibility to Local Centres (ALS):			
poor	667 (55.8)	53.4	0
good	528 (44.2)	46.6	1
Accessibility to District Centres (ADS):			
poor	913 (76.4)	65.9	0
good	282 (23.6)	34.1	1

Length of residence (LOR) corresponds to the amount of time the household lived in the home they occupied when the Cardiff Panel was conducted. From Table 3.2.2 it is apparent that almost 50% of the observations are accounted for by individuals who lived in their 1982 residences for ten or more years whilst only 18% of the observations are for households with length of residence of zero to less than three years. These values are consistent with those of the Cardiff Consumer Panel in which 55% of the panellists lived in their 1982 residences for ten or more years and only 18% lived in their homes for less than three years. The effect of length of residence on shopping behaviour is somewhat ambiguous. On the one hand, it is reasoned that length of residence provides a measure of the degree of knowledge a household may have about available store alternatives and the more alternatives known to be available the greater the possibility of store switching. Alternatively, it is also reasonable that the longer the length of residence the more developed the household's preference structures for different shopping alternatives, thereby resulting in a more habitual store choice.

Freezer ownership is measured by the fridge with freezer (FFO) and separate deep freezer (DFO) variables. Approximately 65% of the observations are for households who own a fridge with a freezer, which is roughly equivalent to that of the Cardiff Panel. The percentage of observations for households who own a separate deep freezer is 59%, slightly higher than in the overall Panel, 54%. Davies and Pickles (1987) suggest that freezer ownership is an important variable in the link between income and shopping frequency and Uncles (1987) reasons that deep freezer ownership results in a tendency for less frequent shopping trips with more items bought on any one occasion. From the discussion of Chapter One, it is apparent that deep freezer ownership has altered individual purchasing patterns by enabling consumers to maintain higher levels of grocery inventory. Thus it can be hypothesized that individuals who own a freezer will make fewer shopping visits and will tend to favor the larger stores (ie. district centres) which have more extensive product lines.

Three variables are considered in this analysis which may provide insight into the influence of car availability. As listed in Table 3.2.2, these are the number of cars owned by the household (NCAR), the panellist's *perceived* use of a car for grocery shopping (USEC), and the panellist's possession of a driver's license (LIC). The percentage of observations occurring for each of these variables is approximately equal to those seen in the Cardiff Panel (see Table 3.2.2). Previous investigations indicate that car availability has a significant impact on both shopping frequency and purchasing patterns (Dunn & Wrigley, 1983; Moore, 1989; Reader & Uncles, 1988; Wrigley & Dunn, 1988; 1985d). Car availability likely facilitates the transportation of large amounts of purchased items as well as bulky items, encouraging larger inventory buying and hence reducing the overall number of trips to both local and district centres. Car availability also affords increased mobility and likely increases the number of available spatial alternatives which, in turn, may increase the tendency to visit more distant centres. For example, Moore (1989) found that Cardiff residents without a car were markedly more sensitive to variations in distance than those with a car and car owners were more concerned with the variety of goods offered by a store rather than its distance from the household.

However, Davies and Pickles (1987) found that the effect of car availability on shopping frequency was not statistically significant and reasoned that the reduction in trips due to the increased transportability of products was countered by the increased mobility encouraging more trips. It should be noted that, despite the research work cited above, it is difficult to operationalize any general measure of accessibility in the Cardiff data because the relationship between the locations of the study areas and the locations of the shopping alternatives is such as to tend to negate the effects of those variables, such as car availability, which affect accessibility. Therefore, in this thesis, it is hypothesized that car availability will effect durations between store switches partly through influencing the frequency of the store visits and partly though influencing the range of store alternatives available.

Age (AGE) of the panellist is also considered as a possible influence on store switching behaviour, although previous examination of the effects of age structure on shopping behaviour is inconclusive (Shepard & Thomas, 1980). The age structure of the observations is different from that of the Panel, with 62% of the observations for panellists less than 44 years old whilst only 52% of the Panel reflects persons in this age group (see Table 3.2.2). Moore (1989) dismisses age as an important influence on the shopping behaviour of Cardiff residents because he found that there was no clear relationship between store preference and variation in a consumer's age. However, it is possible that older persons have fewer spatial alternatives due to mobility constraints, especially if a car is not available, and thus may be more confined to local centre shopping. Furthermore, it can be hypothesized that younger panellists are more likely to be exploratory in their shopping behaviour whereas older panellists may be more habitual in their choice of store, due to greater familiarity with the available alternatives. Age may also be linked with other variables such as length of residence, household size, the presence of children and employment status, all of which are believed to be important factors in shopping patterns.

Previous investigations using the Cardiff Panel considered the effect of marital status in conjunction with employment status (Dunn & Wrigley, 1988; 1983; Reader & Uncles, 1988; Wrigley & Dunn, 1985d) but in this study the influence of marital status (MART) and employment status (EMPLY) is examined separately. The vast majority of the observations are for panellists that are married, ie. over

85%, which is a slightly higher percentage than the percentage of married panellists in the Cardiff Panel (see Table 3.2.2). In terms of inventory levels, the marital status (MART) of a panellist is linked to household size but marital status may also influence the time available for shopping since married couples can divide household responsibilities (like shopping) whereas single persons may be more restricted by time constraints. On the other hand, married households may have more responsibilities than single persons, for example due to household maintenance or if children are present in the household, and thus may have greater time constraints than single panellists, who may have greater flexibility with their time. Employment status (EMPLY) is also likely to be an important influence on switching behaviour because it can result in time constraints for shopping which may not occur if an individual was unemployed. In other words, full–time employment confines the number of hours available for grocery shopping which has been found to encourage larger, less frequent shopping trips (Davies & Pickles, 1987; Uncles, 1987). Furthermore, since time constraints associated with employment are consistent, (for example, working nine to five, five days a week) less variation in the duration between purchases may be expected.

In general, income (INC), as well as being a measure of household affluence is also a surrogate measure for other, less tangible, household attributes such as the ability of an individual to plan and organize shopping activities. The percentages of income levels seen in the observations is comparable to the percentages of household income levels of the Cardiff Panel, with the exception of a slightly greater percentage of the Panel associated with the lowest income category (2.7%) than in the observations (0.9%) (see Table 3.2.2). Davies and Pickles (1987) postulate that the lack of monetary constraints of higher income households allows for larger inventory buying on any one store visit which, in turn, may encourage greater incentive to anticipate consumption needs and thus avoid 'filler' trips. This implies that 'topping up' household inventory at local stores would be less frequent with higher income households, resulting in fewer switches between local and district stores. However, such reasoning could also be applied to lower income households who need to plan anticipated consumption and organize shop visits to meet the constraints of a limited budget and thus may tend to avoid expensive 'filler' trips to convenience (local) stores, thereby decreasing the number of store switches. Given the lack of monetary constraints for higher income households and the monetary limitations imposed on lower income households it is hypothesized that the middle income households are more likely to be the least planned in their shopping behaviour and so are more likely to switch between both types of centres.

The presence of children in a household (labelled (YC) and (OC) in Table 3.2.2) is obviously related to household size (HSZ), and both of these characteristics are likely to prove good indicators of the rate of inventory depletion and the rate at which unanticipated shortages prompt local centre trips (Davies & Pickles, 1987). The presence of children may also restrict mobility and may confine shopping trips to local centres, especially if a car is unavailable for shopping which, in turn, implies that households with children may be less likely to visit district centres. On the other hand, the presence of children may restrict the time available for shopping and perhaps promote less frequent, more regular shopping trips which infers visits to district centres may be more likely, particularly if a car is available. Approximately the same percentage of observations are seen for households with young children (23%) as are households with young children in the Cardiff Panel (19%). On the other hand, comparatively fewer of the observations are for households with older children (OC), 59%, compared to the percentage of households with older children in the Panel, 45%. Younger children (YC) are likely to be a greater constraint on mobility and time than older children and so the effect of younger children on shop visits is likely to be more pronounced than the effect of older children. Older children (OC) are more likely to be in school, thereby being less of a constraint on mobility but may still effect the time available for shopping, although this would also likely depend on the employment status of the caregiver. Older children are also more likely to be shoppers themselves and hence would not only be less of a constraint on mobility than younger children but may also contribute to household purchasing.

Increasing household size (HSZ) may promote shopping trips to district centres as stores associated with these areas offer a wider selection of goods which would satisfy the tastes and preferences of different household members. However, larger households are also likely to be associated with greater consumption rates than those of smaller households which may necessitate more frequent shopping trips to both types of centres. This, in turn, may lead to prevalent store switching behaviour although it is likely that the larger stores associated with district centres may encourage shopping trips to these areas, thereby decreasing the number of shopping trips, but this will likely depend on car availability. The majority of the observations are for 3 to 5 person households (66.2%) which is comparable to the number of such households in the Panel (61%). It should be noted that relatively fewer observations reflect smaller, 1 to 2 person households (19%) than the number of such households in the Cardiff Panel (32%) and that 14% of the observations are for large, 6 to 7 person households whilst only 7% of the Panel is comprised of such large households.

The frequency of weekly shopping (FREQ) variable provides a measure of the panellists *perceived* level of shopping activity. Approximately, 46% of the observations reflect panellists who felt they shopped for grocery items 2 to 4 times a week, which is comparable to to the number of households seen in the Cardiff Panel (see Table 3.2.2). The frequency of shopping is hypothesized to reflect store switching behaviour in that the shoppers who perceive themselves as frequently buying may tend to switch centres more often than regular, once–a–week shoppers. Frequent shoppers have greater potential to visit different stores simply because they buy more often and thus are likely to have a greater range of store trips which may result in a higher store switching rate than less frequent shoppers. Less frequent, regular shoppers often shop only once–a–week and such behaviour may reflect individuals who are restricted by time and mobility constraints. However, it should be noted that, in general, consumers tend to underestimate their purchasing frequency and hence the perceived frequency of weekly shopping variable (FREQ) may not reflect actual shopping behaviour.

The accessibility of households to local and district centres (ALS and ADS, respectively) is derived for each of the 424 households based on the accessibility measures of the study areas they are associated with. Residents of Rhiwbina, Llanederyn, Rumney and Heath have poor accessibility to local centers while panellists living in Llanrumney, Whitchurch, Cathays and Roath have good access to local stores. In terms of district centres, only the residents of Llanederyn, Cathays and Roath have good access. It is reasonable to assume that the more accessible a type of centre is the more likely it will be visited. From Table 3.2.2 it is apparent that accessibility to local centres does not necessarily favor them over district centres as shopping destinations since approximately 44% of the observations are households with good accessibility to local centres compared to 56% for those with poor accessibility. These percentages of accessibility to local centres is roughly equivalent to those of the Cardiff Panel, wherein 53% of households have poor access and 47% of households have good access. On the other hand, only 24% of the observations were for households with good accessibility to district centres (34% of households in the Panel) compared to 76% for households with poor accessibility to district centres (compared to 66% of households in the Panel). Therefore, it appears that district centres dominate the observed shopping patterns and are an important destination choice for Cardiff residents in that poor accessibility to district centres does not necessarily dissuade trips to these areas. Instead, poor accessibility to district centres may increase the tendency to visit local centres, which combined with the overall dominance of district centre purchases, would increase the number of observed switches between local and district centres. Households with good accessibility to district centres tend to have their shopping trips dominated by this centre type, resulting in fewer switches between local and district centres.

From the discussions above it is apparent that many of the household variables can be hypothesized to either increase or decrease the duration between centre switches. The seemingly contradictory arguments for each of these variables result from the fact that *duration* in this thesis represents a surrogate measure of a combined purchasing rate and store switching rate. It may be difficult to discern the effect of a variable on duration if the effect on purchasing frequency is reasoned to increase duration whilst the effect on store switching is thought to decrease duration, or vice versa. On the other hand, if a variable is hypothesized to influence both the purchasing rate and the store switching rate in the same manner (ie. both rates wither increasing or decreasing duration), it is not as difficult to assess the effect of the variable on duration. For example, for a panellist who is characterized as a frequent purchaser (ie. has a high purchasing rate) and who also switches between district and local stores frequently (ie. exhibiting a high store switching rate) then short durations between store switches would be expected. Conversely, if a panellist is an infrequent purchaser (ie. possesses a low purchasing rate) and remains loyal to a particular store type (ie. has a low store switching rate) long durations between store switches would be more likely. Alternatively, if a panellist is characterized as having a low store switching rate but their purchasing frequency is high, then medium length durations between district and local centre switches could be expected if both of these rates have a relatively equal influence on shopping behaviour. On the other hand, the same medium length durations could result from a high store switching rate observed for a panellist who possessed a low purchasing rate. In some cases the influence of purchasing rate may override that of the store switching rate so that, in this example, shorter durations would be expected whereas if the influence of the store switching rate outweighs that of the purchasing rate longer durations would be more likely to occur. These types of situations can be complicated further if the relative influence of purchasing rate and store switching rate change over the length of the study period.

3.3 Analysis Outline

In the analysis of an extensive event history data set, the first stage is exploratory, the purpose being the identification of which covariates (ie. explanatory variables) correlate with the observed behaviour. The first phase of the exploratory analysis conducted in this thesis concerned identification of the covariates which were likely to be important influences on shopping behaviour. The second phase of the exploratory analysis investigated further the influence of particular covariates whose effects were thought to not likely be proportional over time. The second stage of this analysis concerned the statistical evaluation of the covariates and description of the influence of duration dependence on store choice behaviour using an event history modelling approach.

3.3.1 Exploratory Analysis

The initial phase of the exploratory analysis made extensive use of the **Kaplan–Meier** (KM) estimate (a.k.a. product–limit estimate) of survivor functions. KM estimates were derived for each of the covariates by stratifying the observations by each covariate, in turn, and calculating the KM survival functions associated with each stratum. The estimates for each of the stratified covariates were then plotted over time and the resultant KM **survival curves** were visually analyzed to determine whether the covariate may be influencing duration. If the stratum for a covariate were seen to distinctively differ from one another then it was assumed that the covariate was likely to be an important influence on duration and thus was retained for the remainder of the analysis. On the other hand, if the observed difference between strata was found to be indistinct, various re–categorizations of the variable were made. If these re–categorized variables failed to produce strata that were different, it was assumed that the variable was unlikely to be an influence on store choice behaviour and it was not included in further analysis.

The second phase of the exploratory analysis used a stratified version of Cox's (1972) proportional hazards model to investigate those covariates which were thought to possibly violate the proportionality assumption of proportional hazards models. Furthermore, it was also believed that the study areas from which the Cardiff Consumer Panel was derived may inherently differ in terms of socio–economic status and that such differences may not adequately be represented by the measured covariates described in Section 3.2. Consequently, the study areas were also used to define strata in this second phase of exploratory analysis.

This analysis consisted of estimating survival functions, using a stratified Cox model, for each stratum of the covariates under investigation. These survival functions were then used to derive estimates of the integrated hazard rates for each stratified covariate. When plotted against time, these integrated hazard rates should exhibit approximately constant separation between stratum if the assumption of proportionality holds.

3.3.2 Event History Modelling

Initial evaluation of duration dependence in store choice behaviour was concerned with the fit of parametric models (see Section 2.5.4) to the observations (ie. durations) without including the covariates identified in the exploratory analysis. It should be noted that throughout the event history analysis, 1,182 of the original 1,195 observations were examined. This difference is due to the elimination of observations from the 1,195 data set for which the panellist's length of residence (LOR), possession of a fridge with a freezer and possession of a separate deep freezer (DFO) were unkown, which corresponded to 13 observations. Parameter estimates for the exponential, Weibull, Gompertz, log–normal and log–logistic models were derived and the associated hazard rate curves were produced and evaluated. These durations were then disaggregated according to a variable representing store type to determine if different distributional forms were associated with local stores as opposed to district stores. The parameter estimates for these disaggregated durations were obtained using the same five different parametric models and the corresponding hazard rate curves for these durations were produced and the fit of the models was assessed.

3.3.3 Event History Regression Modelling

This part of the analysis concerned the influence of covariates, firstly, on *all* durations (ie. those representing switches from both local and district stores) and secondly, the durations disaggregated by store type. Analysis of the influence of the covariates was initially restricted to examining the effects of those exogenous variables identified as likely influences on store switching behaviour by the exploratory analysis. The covariates representing the number of interpurchases (NIP) and income status (INC) were not initially included in model estimates but were introduced separately in the second and third phases of the event history regression analysis. Furthermore, a variable representing the store type associated with each of the observed durations (ie. STYP) was also added to the list of covariates.

The Cox model (equation (2.5.40)) and a stratified version of the Cox model were used to examine the durations to determine if inherent differences in the baseline hazard rates existed for the durations associated with local store choice as opposed to the durations associated with district store choice. The parameter estimates associated with the exponential, Weibull, Gompertz, log–normal and log–logistic parametric models were also derived for both *all* durations and the disaggregated durations to determine if differences in the importance of covariates on affecting these different durations occurred. Furthermore, the estimated hazard rate curves calculated at the mean of the covariates were plotted to provide insight into the distributional form of duration dependence associated with store choice behaviour.

3.3.4 Endogenous Factors

The number of interpurchases (NIP) covariate is an endogenous variable which serves as a proxy measure for purchasing frequency associated with a particular duration length. Recall from Section 3.2 that the number of interpurchases (NIP) affects household grocery inventory as it corresponds to the number of consecutive purchases made for the product category baked beans which occur while a panellist is *loyal* to a particular store type (ie. district or local stores). Consequently, the durations as well as the durations disaggregated according to store type were investigated and the covariate representing the number of interpurchases (NIP) was included in the event–history models examined previously. Coefficient estimates from the Cox model and the exponential, Weibull, Gompertz, log–normal and log–logistic parametric models were obtained and assessed for changes in the effects of significant covariates. Also, parameter estimates were derived for the parametric models and the corresponding hazard rate curves were produced and examined to determine if changes in the distributional form of duration occurred when the number of interpurchases (NIP) covariate was included in model estimates.

3.3.5 The Influence of Income

The effect of income status (INC) on the durations was examined separately from the other covariate evaluations because 367[2] of the observations in the data set were for panellists who did not report their income in the initial questionnaire. Therefore, it was deemed necessary to establish if any inherent differences existed for the durations associated with panellists who did report income as opposed to those who did not report income. Examination of the effect of income status was conducted in three steps.

Firstly this investigation was concerned with identifying the influence of income reporting and was examined by including a dummy variable (IREP) which reflected whether income was reported (IREP=1) or not reported (IREP=0) by the panellist. Parameter estimates were derived for *all* durations as well as the disaggregated durations using the models that were found to best represent the durations when both the number of interpurchases (NIP) was not included as a covariate and when it the number of interpurchases (NIP) was included as a covariate.

Secondly, this examination was concerned with evaluating the possibility of

[2]In Table 3.2.2 (page 157), 373 of the 1,195 observations are recorded for panellists who did not report income status which translates to 367 out of the 1,182 observations, ie. after those panellists who did not report length of residence (LOR), fridge with freezer ownership (FFO) and deep freezer ownership (DFO) are removed from the study data set.

inherent differences between the characteristics associated with panellists in the entire data set (1,182 observations), those who did report income (815 observations) and those who did not report income (367 observations). The covariates which were included to identify such differences were the same as those examined in the initial phase of the event history regression analysis and included the endogenous variable corresponding to the number of interpurchases (NIP). Coefficient estimates were obtained using the log–logistic parametric model and the results were evaluated. The log–logistic was used as it was found to best describe the durations associated with each of the three sample sizes.

Lastly, explicit examination of the influence of income status (INC) on *all* durations as well as the durations disaggregated by store type was considered. Therefore, in addition to the covariates listed above, the income status (INC) variable was included in a log–logistic model and the resultant coefficients were examined to determine if income status (INC) was a significant influence on the duration between store switches.

3.4 Software Description

Developments in computer power and storage capabilities have enabled the very large data sets generated by longitudinal records to become manageable, although checking, editing and processing longitudinal records can still be time consuming and expensive. Developments in computer software and statistical modelling have resulted in more effective methods for analyzing longitudinal data but, in general, the provision of software still lags behind developments in theory and method (Matthews, 1989). The usefulness of any technique for analyzing longitudinal data can be severely limited by the availability of appropriate estimation routines. Conventionally, the usefulness of software for longitudinal analysis resides in its flexibility to accommodate a range of model estimation routines and its ability to handle both censored observations and time–varying exogenous variables. There currently exists a number of computer packages which are useful to event history analysis and an important part of this research work involved exploring the merits of the available packages.

Evaluation of the available software packages was based on the methodological requirements of this analysis. Description of the particular methods which were used in this research are given in Section 3.3, but essentially various models (both parametric and partially–parametric) were investigated to determine their adequacy in representing the empirically observed durations in the store choice data. Therefore, the selected package had to be able to accommodate a range of event history models and provide evaluation procedures for assessing model estimates. Graphical techniques used for exploratory analysis are fundamental to event–history research and so a package which produced graphical plots was desired. While most of the available software packages produced survival and hazard rate curves, it was decided that the quality of these graphs was insufficient for this exploratory analysis. Therefore, one requirement became the ease with which derived data estimates could be saved and formatted for subsequent graphing in AXUM, the graphics package used in this analysis. Graphical techniques are useful indicators of the influence of covariates on duration times (Blossfeld et al., 1989; Kalbfleisch & Prentice, 1980), but in subsequent analysis statistical tests of the significance of a particular model form was required. Furthermore, the selected package had to be able to handle right–censored observations in estimation routines, allow for variable transformations of input data and accommodate selection of subsets of data for investigation.

The capabilities investigated for each package are summarized in Table 3.4.1 (page 175). The 'standard' packages listed in Table 3.4.1 refer to ones which are well known in the social science and geographical research community, unlike the 'specialty' packages which are small, relatively unknown, special purpose packages which were obtained directly from their (academic) developers. Typically, 'standard' packages are high level, multi–purpose statistical packages which contain certain procedures capable of performing some aspects of longitudinal data analysis. All of the 'standard' packages listed in Table 3.4.1 are generally well–supported by manuals and on–line help, with the exception of GLIM which is essentially an open–ended program that requires complex mathematical operations and is generally not well supported outside the UK. The 'specialty' packages are products of small research teams seeking to improve upon the longitudinal analysis techniques of the 'standard' packages and are essentially 'low–budget' software packages which lack technical support. Matthews (1989) outlines the main features of most of the packages listed in Table 3.4.1 but some factors are worth mentioning here.

At the time of investigation, and based on Matthews (1989), SPSS–X and BMDP were the least desirable as they did not estimate the parametric models used in this analysis. At an elementary level, the SURVIVAL procedure of SPSS–X (1986) produced life tables, graphs of survival functions and could stratify subsets of sample data which could then be written to a file for plotting in a high–quality graphics package. BMDP (Dixon, 1985) produced life tables and survival function estimates, comparable to those of SPSS–X, but, in addition, could be used to assess the influence of covariates (both static and time dependent) on survival rates using Cox's (1972) partially–parametric proportional hazards model (Section 2.5.6). A useful feature of the BMDP package was that it could automatically convert dates which represent entry into and exit from the study period into 'time–on study' variables and generating the corresponding censoring information.

Unlike SPSS–X and BMDP, GLIM and SAS estimated most of the models

Table 3.4.1: Summary of software exploration findings

	STANDARD PACKAGES				SPECIALTY PACKAGES		
	SAS	SPSSX	GLIM	BMDP	RATE	SURVREG	LIMDEP
PARAMETRIC MODELS:							
Log-normal	Yes		Yes			Yes	Yes
Log-logistic	Yes		Yes			Yes	Yes
Exponential	Yes		Yes		Yes	Yes	Yes
Weibull	Yes		Yes			Yes	Yes
Gompertz			Yes		Yes		Yes
Gamma	Yes				Yes		Yes
PARTIALLY PARAMETRIC MODELS:							
Cox model	Yes		Yes	Yes	Yes	Yes	Yes
Stratification	Yes	Yes		Yes		Yes	Yes
FEATURES:							
Life Tables	Yes	Yes		Yes		Yes	Yes
KM Estimation	Yes	Yes		Yes		Yes	?[1]
Censoring	R	R	R	R	R	R[2]	R
Data Transformations	Yes	Yes		Yes		Yes	Yes
Time-varying covariates	Yes		Yes	Yes	?[3]	Yes	?[4]
Stepwise regression	Yes	Yes		Yes		Yes	Yes
Diagnostic Plots	Yes	Yes	Yes	Yes		Yes[5]	Yes[6]
Goodness-of-fit tests	Yes	Yes		Yes	Yes	Yes[7]	Yes
User Specified Parameters			Yes		Yes	Yes	Yes[8]

Notes: [1] problems were encountered with duration output
[2] also allows for more general ensoring
[3] allows for time dependent covariates in parametric models but not the Cox model
[4] allows for time-varying covariates in Cox model but not parametric models
[5] does not plot hazard function
[6] user-defined intervals for plotting do not work
[7] does not produce log-rank chi-squared estimates
[8] except for the Gompertz model

used in this analysis. GLIM, developed by Baker and Nelder (1978) was the most flexible of the 'standard' packages and could accommodate user–defined modules which would be particularly useful for tailoring the software to a particular study. However, GLIM required complex programming on the part of the user. On the other hand, SAS (1980) included an available library of procedures for analyzing longitudinal data and produced statistical tests of model adequacy. However, SAS did not estimate a Gompertz model and was also limited in that it did not allow for user–defined parametric estimates to be specified as part of the data input.

All of the 'standard' packages discussed above required a great deal of time in order to become familiar with the data structures and command language specific to the package. Therefore, since the available 'standard' packages possessed limitations as well as a steep 'learning curve' associated with becoming familiar with these packages, the adequacy of the 'specialty' packages was examined, even though their technical support was limited.

RATE 2.0 (Tuma, 1980) was a Fortran program which estimated parameters in continuous–time stochastic models and was designed specifically for event history analysis. RATE was limited to estimation of only four different types of models and special data preparation was required for partial likelihood estimation associated with the Cox model. Generally, RATE 2.0 was found to be too cumbersome for this analysis, although version 3.0 is promised to be a major upgrade which allows data to be structured in a variety of ways, incorporates a greater number of model estimation routines and enables data transformations. RATE 3.0 was not available at the time this study was conducted.

SURVREG (SURVival analysis with REGression) (Preston & Clarkson, 1988) was a flexible interactive Fortran program useful for the analysis of survival and reliability data. The program could be used to perform parametric and nonparametric maximum likelihood estimation for censored data with (or without) covariates, and allowed model construction options which aided understanding of the effects of covariates on survival rates. As shown in Table 3.4.1 SURVREG estimated most of the parametric models desired in this study, including the exponential, Weibull, log–normal and log–logistic distributional models. Nonparametric methods included both Kaplan–Meier and generalized Kaplan–Meier estimation (see Preston & Clarkson, 1988 for details), and SURVREG produced life table data as part of the output. SURVREG was easy to use and had many options including a powerful tool for analyzing censored data in which data are classified into one of three types, depending on the censoring pattern. Other useful features available in SURVREG were forward and backward stepwise selection procedures for covariates in the Cox model, plotting options for survival curves, integrated hazard plots, log integrated hazard plots and $\log_{10}(t)$ versus standardized quantiles (ie. QQ plots), the ability to perform data transformations and include user–defined variables as well as calculation of the approximate confidence intervals for quantiles and reliability estimates.

LIMDEP (Greene, 1990) was a flexible econometric software package which could be used to estimate a number of models including purchase incidence models (Section 2.2.4), discrete–choice models (Section 2.3) and the range of continuous–time event history models examined in this research. LIMDEP was primarily orientated toward interactive use and was strictly command driven, in a manner similar to that of MINITAB. LIMDEP allowed for both parametric and nonparametric maximum likelihood estimation of duration data which may (or may not) include covariates and included a number of goodness–of–fit options for testing the significance of a particular model. All of the parametric models desired for this study were available in LIMDEP (see Table 3.3.1) including the log–normal log–logistic, exponential, Weibull and Gompertz models. Nonparametric methods included Kaplan–Meier estimation of duration times, which could be stratified according to a particular variable. In addition, Cox's proportional hazards model was available and could include time–varying covariates, stratification, and/or fixed parameter vector values in model estimates. LIMDEP's output options included life tables, iterations for parametric estimates and chi–squared values associated with the log–rank test for all model estimation routines. Other commands could be used which save the hazard rate, integrated hazard rate and the associated duration times for plotting in alternative graphics packages.

Of the 'specialty' packages listed in Figure 3.4.1, this thesis utilized both LIMDEP and SURVREG, since both of these packages adequately accommodated the analysis requirements of this research. A problem was encountered in LIMDEP's graphical plots associated with the Kaplan–Meier (KM) estimate, due to a data output error in the program. KM survival estimates were therefore calculated in SURVREG to produce the exploratory findings which were used in the remainder of this analysis. Subsequent analysis used both LIMDEP and SURVREG and, consequently, tests of the consistency between these two packages were necessary. Using the published carcinogenesis data of Kalbfleisch & Prentice (1980:82), as well as the data of this study, identical estimates for these data sets using both parametric and nonparametric estimation routines were obtained. Thus confidence was placed in using both SURVREG and LIMDEP in this research.

CHAPTER FOUR

RESEARCH FINDINGS

4.1 Exploratory Data Analysis

The first phase of the exploratory analysis made extensive use of Kaplan–Meier (KM) survival function estimates. KM estimates are 'nonparametric' in so far as they make no assumptions regarding the distribution of event times. In KM estimation, observations are ranked according to their duration lengths and KM estimates are then calculated on these ranked durations. KM estimation treats right–censored observations as occurring after non–censored observations at a particular duration value. Consequently, right–censored observations only decrease the 'risk set' of later occurring events. If the last duration value has only censored observations, then the KM estimate of the survival function is defined over the largest duration in which non–censored observations occurred. This method of handling both censored and non–censored observations results in a step function between the duration times with a KM estimate of the survival function calculated at each step.

Therefore, in KM estimation, the conditional probability of experiencing an event at each duration is, in effect, assumed to agree exactly with the observed relative frequency of failures at that duration. In other words, the KM estimate of the hazard rate is a conditional probability where the hazard, $\hat{h}(t_j)$, is the probability of experiencing an event at duration t_j conditional upon being at 'risk' at t_j. This may be expressed as:

$$\hat{h}(t_j) = d_j \;/\; n_j \;, \tag{4.1.1}$$

where d_j is the number of events ('failures') at duration t_j, and n_j is the number at 'risk', ie. the number of observations which have neither failed nor been censored immediately prior to duration t_j. The corresponding estimate for the survivor function is:

$$\hat{S}(t_j) = \prod_{i=1}^{j}(n_i - d_i) \;/\; n_i = \prod_{i=1}^{j}(1 - \hat{h}_i) \;, \tag{4.1.2}$$

where $\hat{S}(t_j)$ is the Kaplan–Meier estimate reflecting a monotone decreasing function such that $0 \leq S(t_j) \leq 1$.

KM estimates can also be generalized to include a vector of covariates, ie. $\hat{S}(t_j;\ \mathbf{x})$ so that the probability of survival is specific to particular values of exogenous variables. Such KM estimates are essentially descriptive measures useful for examining the durations of different members of the population, ie. as reflected in the measured covariate values. When these KM survival estimates are plotted over time, **survival curves** are produced. Survival curves are a fundamental analysis tool in duration research (Blossfeld et al., 1989; Kalbfleisch & Prentice, 1980; Kiefer, 1988; Odland & Bailey, 1990; Odland & Ellis, 1990; Tuma, 1982). However, derived plots of the integrated hazard and the logarithm of the integrated hazard are also frequently used because they generally produce smoother curves and hence are easier to interpret than survival curves. For example, in an exponential distribution, the hazard rate is assumed to be constant and thus the integrated hazard is linear with time. This integrated hazard can be estimated by:

$$\hat{\Lambda}\,(t_j) = \sum_{i \leq j} \hat{h}\,(t_i) \;, \tag{4.1.3}$$

or alternatively as:

$$\hat{\Lambda}\,(t_j) = -\ln \hat{S}\,(t_j) \;. \tag{4.1.4}$$

The estimate of the integrated hazard can then be used to assess the validity of the exponential model assumptions on the data set being examined. In other words, if the integrated hazard rate produced for the data is linear with time, then it is reasonable to assume that the exponential model assumptions hold. Similarly, integrated hazard plots can be used for evaluating the other parametric models (described in Section 2.5.4) to assess their appropriateness to a particular data set.

In this study, KM survival curves were used to identify the covariates which may be important influences on store choice behaviour. This evaluation was achieved by **stratifying** the sample observations by each covariate in turn and calculating the KM estimate, $\hat{S}(t_j;\ \mathbf{x}_i)$, for each of the i strata. The categories defining the strata for each of the variables analyzed are as defined in Table 3.2.2 (page 157), except for those corresponding to the number of interpurchases (NIP) variable which are given in Figure 3.2.2 (page 155). Visual analysis of the differences in survival function estimates for the strata indicate the degree to which that covariate may be influencing duration. For example, to evaluate whether or not car availability affects duration, the binary covariate representing car availability was used to stratify the sample. In this situation, KM estimation makes the assumption that the two groups (ie. those with a car available and those without a car available) are homogeneous with regards to all other factors. KM estimates for the survival functions, calculated separately for each of the two strata and plotted against time, can then be assessed to determine if the curves are distinctively different from one another. If the resultant curves were found to be obviously different it can be assumed that car availability it likely to be an important influence on the survival rate, ie. the duration until a store switch occurs. On the other hand, if the observed difference between strata was found to be indistinct, various re–categorizations of the variable were made. If these re–categorized variables failed to produce strata that did not distinctively differentiate between the covariate categories then it was assumed that the variable was not likely influencing the duration between store switches and thus the variable was dropped from further analysis. Visual inspection of the difference between survival curve stratum can be supplemented by statistical tests such as the log–rank and Wilcoxon tests. This analysis, however, being exploratory, only relied only on visual analysis.

Based on the visual analysis of survival curves, 12 of the 17 covariates discussed in Section 3.2 appeared to possibly influence duration. These were:

NIP – the number of interpurchases,
LOR – the length of residence,
DFO – separate deep freezer ownership,
LIC – possession of a driver's license,
AGE – the panellist's age,
MART – marital status,
INC – income status,
HSZ – household size,
YC – the presence of young children (those less than 5 years),
OC – the presence of older children (those 5 to 15 years),
FREQ – the *perceived* frequency of weekly shop visits, and
ADS – the accessibility to district centre stores.

The survival plots produced for each of these variables is shown in Figure 4.1.1 (page 183) and the survival curves produced for those variables which were dropped from the study are given in Figure B.1 of Appendix B. It should be noted that the covariate categories shown in Figure 4.1.1 were chosen to maximize the differences between strata whilst attempting to maintain a realistic number of observations in each category.

The relationship between the number of interpurchases (NIP) and survival

Figure 4.1.1: Estimated KM survival curves for the variables found to likely influence the duration between store–type switches

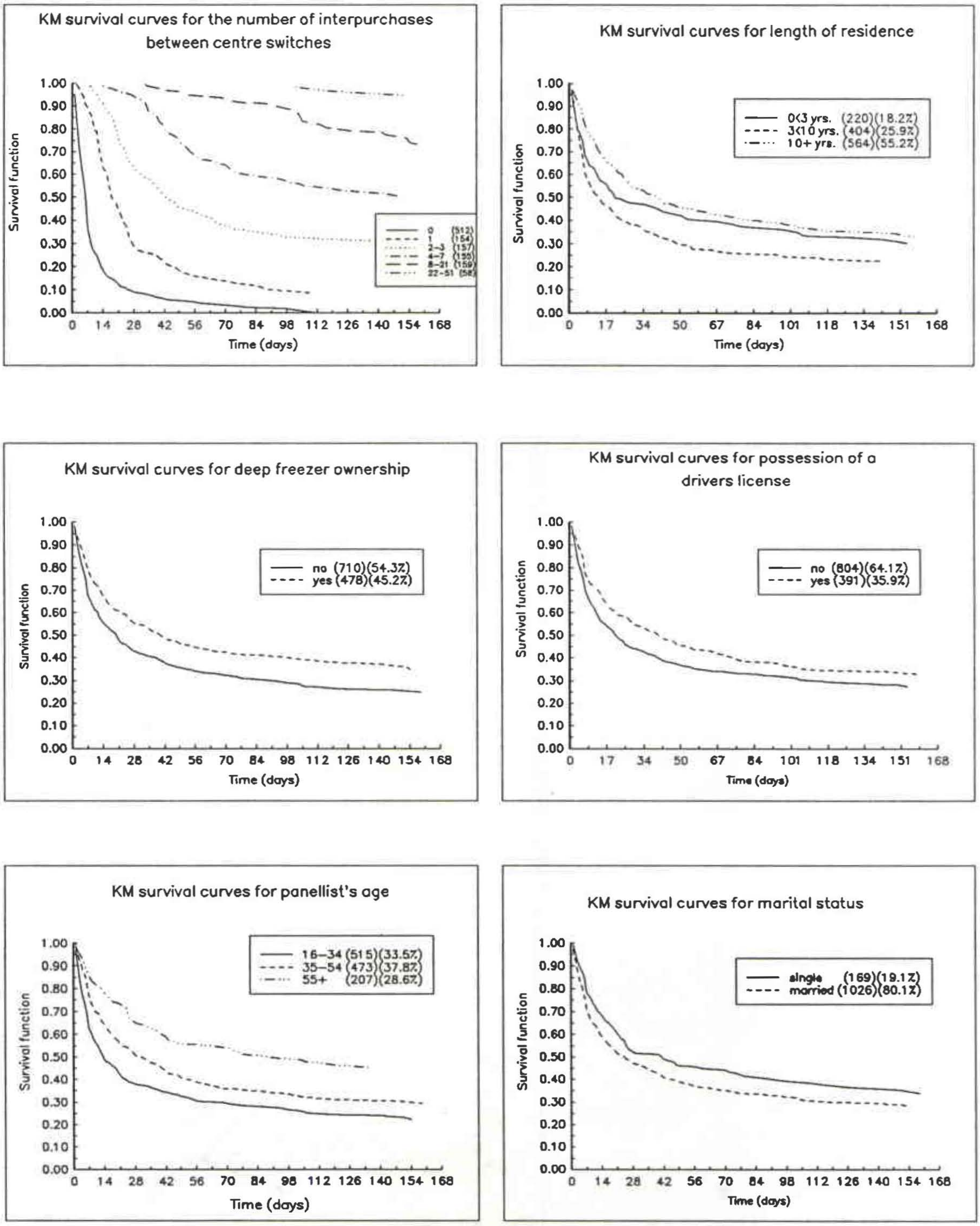
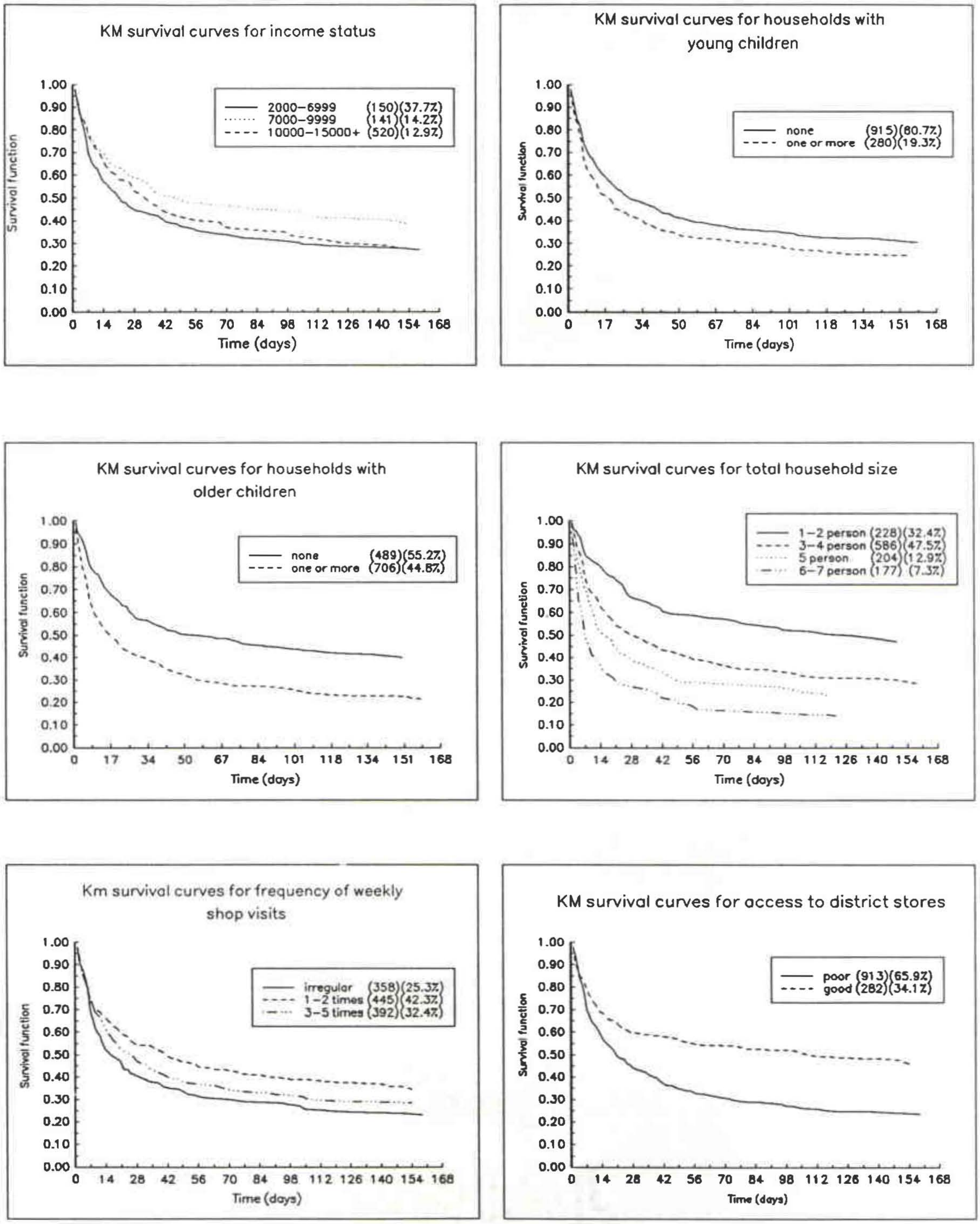


Figure 4.1.1 continued...



(note: numbers in parentheses refer to the number of observations in the study study data set whilst percentages in parentheses reflect the corresponding percentages in the Cardiff Consumer Panel) rate, as illustrated in Figure 4.1.1, is a direct one in the sense that as the number of interpurchases made by a panellist increases so does the probability of survivorship, ie. the longer the duration until a store switch occurs. In other words, as the number of interpurchases increases, the duration obviously increases which, in turn, means that household inventory levels are being replenished by successive trips to the same type of store. This implies that repeat visits to a particular type of store appears to reinforce the choice of that store type. Furthermore, this tendency towards habitual store choice behaviour appears to outweigh the effect of those panellists who purchase infrequently but switch stores very frequently would have on duration. Therefore, it is concluded that the number of interpurchases is likely an important influence on the duration between store switches and hence a covariate representing the number of interpurchases (NIP) was included in the second and third phases of the event–history regression analysis.

Obvious differences between the strata for the length of residence (LOR) variable occur but do not correspond to a direct relationship. As illustrated in Figure 4.1.1, those households which have lived in their 1982 residences for less than 3 years and those who have been there for 10 or more years have relatively similar survival rates as compared to panellists who have resided in their 1982 homes for 3 to 10 years, who exhibit lower survival rates. Panellists with lengths of residence of 10 or more years and those with lengths of residence of less than 3 years exhibit longer durations between store–type switches which may be a result of more habitual store choice behaviour and/or less frequent purchasing behaviour than that associated with panellists who have lengths of residence (LOR) of 3 to 10 years (see Figure 4.1.1). The observed relationship between length of residence (LOR) and survival could also be due to an interaction of this variable with other covariates, resulting in a 'spurious' association between length of residence (LOR) and other factors, and consequently, length of residence may appear to be an important influence on the duration between store switches when it in fact it may not be statistically significant. In order to determine if length of residence (LOR) is indeed influencing the duration between store switches as shown in Figure 4.1.1, this variable was investigated further in the secondary phase of the exploratory analysis.

Evaluation of the KM survival curves for the factors representing the influence of freezer ownership indicate that panellists who possess a separate deep freezer (DFO) have higher survival rates than those who do not possess a deep freezer (see Figure 4.1.1). This relationship *may* be explained by lower purchasing frequencies for households who possess a deep freezer since fewer overall shopping trips need to be made because of the associated increases in storage capacity. Alternatively, households with a deep freezer may have lower store switching rates since they may tend to visit stores which have large stock holdings and thus may be more habitual in their store choice, for example, by often shopping at a district centre store. It is also possible that panellists who purchase a separate deep freezer do so because they *intend* to purchase less frequently and/or plan to shop at larger stores and therefore, these individuals may be predisposed to longer durations between store switches than those individuals who do not possess a deep freezer.

From Figure 4.1.1, it is apparent that possession of a driver's license (LIC) likely influences the duration between store switches. Longer durations between store switches for panellists who possess a driver's license are observed and may result from lower purchasing rates for these individuals as they may tend to purchase more items on any one store visit. Moreover, panellists who have a driver's license may tend to be more loyal to particular stores, for example, stores with ample parking space, in which case lower store switching rates would be more likely which, in turn, would reinforce the influence of lower purchasing frequencies, promoting longer durations between store switches. Furthermore, it appears as though the effect lower purchasing frequencies and/or lower store switching rates outweighs the influence that license possession (LIC) may have on decreasing duration if license possession resulted in higher store switching rates due to increasing the number of available store alternatives.

The KM survival curves for age (AGE) produced in this analysis indicate that age appears to be directly influencing the duration between store switches with younger panellists (16 to 34 years old) having the lowest survival rates, older panellists (equal to or greater than 55 years old) having the highest survival rates and 'middle aged' (35 to 54 years old) panellists having survival rates which lie in between the other two groups. As illustrated in Figure 4.1.1, this relationship between age (AGE) and duration may be the result of lower purchasing rates with increasing age, lower store switching rates with increasing age or a combination of both factors. It may be that mobility decreases with increasing age so that older panellists may have lower purchasing rates which would lead to longer durations between shopping trips. Alternatively, (or additionally), older panellists may be more familiar with the available store alternatives and, as a result, may tend to be 'loyal' to particular stores. Furthermore, the mobility constraints associated with increasing age may lead to habitual choice of only nearby stores. Younger panellists, on the other hand, may be more adventurous in their shopping behaviour, trying a greater variety of stores and/or may shop more frequently.

Investigation of the KM survival curves representing the influence of marital status (MART) on duration indicates that marital status is likely to be an important influence on shopping patterns. From Figure 4.1.1 it is apparent that married panellists have lower survival rates than unmarried panellists. It is possible that married panellists are purchasing for both themselves and their spouse whereas unmarried panellists are more likely to be buying for just themselves, in which case, the former group may be characterized by higher purchasing frequencies than the latter group, which may result in the shorter durations between store switches observed for married panellists. The observed relationship between marital status (MART) and duration may also be due to higher store switching rates for married panellists although there is no intuitive reason why married panellists would switch stores more often than unmarried panellists.

The KM survival curves produced for the income status variable (INC) illustrate an indirect relationship between income and the duration until a store switch. Households in the £2000 to £6999 income category possess the lowest survival rates whilst those earning £7000 to £9999 have the highest survival rates and those earning £10000 or more have survival rates which lie between the other two categories. The 'expected' longer duration times between store switches of higher income households relative to those of lower income households inferred from the work of Davies and Pickles (1987) is not apparent for the highest income category relative to the other income categories. Panellists in the lowest income category may have high purchasing frequencies because monetary limitations restrict purchasing large inventory stocks on any one visit and/or may lead to less loyalty to particular stores since they may plan purchases at stores which offer items on sale. It is possible that panellists in the highest income category can afford a greater variety of stores, for example, more expensive specialty shops, more often than other income groups and this may lead to higher store switching rates. On the other hand, panellists in the middle income category may be more regular once–a–week buyers who tend to visit the same store type. However, the influence of income status (INC) on store switching behaviour may also be accounted for by interaction of this variable with other factors such as, deep freezer ownership, which may provide a more direct measure of household affluence in relation to grocery purchasing. Furthermore, the eight study areas may inherently differ in terms of socio–economic status and such differences may not be adequately reflected in a measure of income alone. Consequently, the influence of income status (INC) on duration was investigated further in the secondary phase of the exploratory analysis and possible differences in the socio–economic status of the eight different study areas was also explored.

The stratified KM survival curves produced to examine the influence of the presence of young children (YC) and older children (OC) on duration indicate that in both situations, the presence of children appears to be an important influence on duration. Households with a young child (YC) have lower survival rates than households that do not have a young child. This relationship may be the result of higher purchasing rates for households with a young child (YC), as the presence of children likely leads to greater consumption rates, but may also reflect higher store switching rates for these households. Similarly, households with an older child (OC) possess consistently lower survival rates than those without an older child and this may reflect higher purchasing rates for households with an older child (OC), higher store switching rates for such households, or a combination of both factors. It is interesting to note that if one compares the two plots for young children and older children, it appears as though the presence of older children (OC) leads to markedly lower survival rates from those households without older children whilst the distinction between households for younger children (YC) is not as strong. This implies that the presence of older children (OC) may be a more important influence on store switching than the presence of younger children (YC).

Evaluation of the KM survival curves representing total household size (HSZ) indicates that household size (HSZ) is directly influencing duration times. Larger households have consistently lower survival rates than smaller households and it seems as though the influence of higher consumption rates, likely associated with larger households, may result in higher purchasing frequencies which, consequently, could lead to shorter durations between store–type switches. However, it is also possible that larger households need to visit a variety of stores to satisfy the tastes of various household members rather than relying on the same type of store for constantly providing adequate stocks. In such a situation, higher store switching rates for larger households would be expected which, in turn, would reinforce the effect of higher purchasing frequencies, leading to shorter durations between store switches.

The KM survival curves for the panellist's *perceived* frequency of weekly shop visits (FREQ) (see Figure 4.1.1) indicate shorter durations between store switches with increasing perceived frequency. This relationship may reflect higher store switching rates for more frequent shoppers since panellists who purchase more often may be more likely to switch stores simply because a greater number of shopping trips occur. It should be noted that the 'irregular' weekly shopping category includes those panellists classified in the Cardiff Consumer Panel as shopping 6 or more times a week as well as those who do not exhibiting any regularity in their weekly purchasing rates (see Table 3.2.2, page 157).

The KM survival curves corresponding to the accessibility to district centres (ADS) variable are seen to have obvious and consistent differences between the strata. Panellists with poor accessibility to district centres have lower survival rates, ie. shorter durations between store switches, than those with good accessibility to district centres. This relationship may be the result of more frequent store switching behaviour for panellists with poor accessibility, who may tend to 'top up' inventory stocks by purchasing at local centres. It appears as though good accessibility to district centres reinforces the choice of that store type, resulting in longer durations between store switches.

It should be noted that the distinction between KM survival curve strata illustrated in Figure 4.1.1 may be somewhat limited representations of the 'true' relationship between survival and duration because of the homogeneity assumption associated with KM estimation. Recall that KM estimation assumes that the subpopulations forming the strata are homogeneous in terms of all other characteristics. This means that the measured covariate used to define the strata is the only factor which is defining the different survival rates. However, in this data set, where we have multiple observations per panellist, those panellists who exhibit lower survival rates contribute more observations than do panellists who exhibit higher survival rates. Therefore, it is possible that the subpopulations defined by a particular covariate may be biased towards panellists with certain characteristics, such as lower (or higher) survival rates, may be over (or under) represented in the estimates. This, in turn, may bias the resulting survival distribution by decreasing (or increasing) the survival rate so that obvious differences between the KM survival curve stratum may be inhibited (or exaggerated) in the resultant plots. Therefore, the KM estimation associated with the initial phase of this analysis simply provided a first heuristic step toward obtaining information about the duration data.

The second phase of the exploratory analysis used a stratified version of Cox's proportional hazards model to determine whether the length of residence (LOR) and the income status (INC) variables as well as the eight study areas might reasonably be incorporated as regression covariates. This was achieved by stratifying the observations by each of these three variables and including the covariates identified in the initial phase of the exploratory analysis as regressor variables in a stratified Cox model. Cox's (1972) model (see equation 2.5.40) requires that for any two covariate values, x_1 and x_2, the corresponding hazard rates are proportional, ie.:

$$h\,(t;\, x_1)\ \alpha\ h\ (t;\, x_2)\ . \tag{4.1.5}$$

The reason length of residence (LOR) and income status (INC) were so investigated was because the KM estimated survival curves for these variables indicated possible non–proportionality (see Figure 4.1.1). Hazard rates which differ markedly from proportionality may be due to interaction between covariates or the influence of unmeasured factors on the measured covariates. Cox's model generalized to examine a stratified sample relaxes the requirement that there is a single underlying hazard rate for the entire population and instead, assumes that homogeneous subgroups exist in the sample, each of which is defined by a different baseline hazard rate:

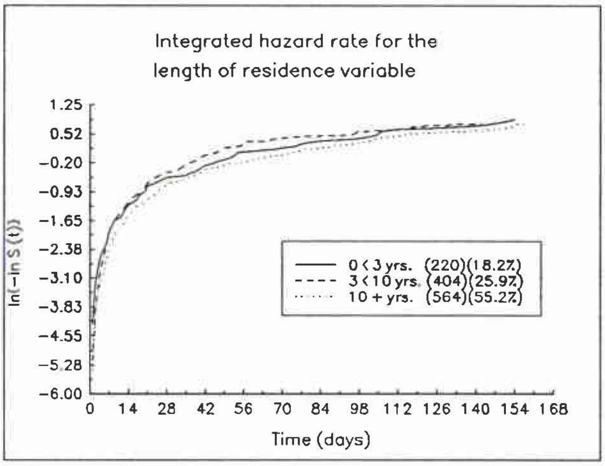
$$\hat{h}(t; \mathbf{x}; \mathrm{i}; \beta) = h_{0\mathrm{i}}(t) \exp(\mathbf{x}\beta) , \tag{4.1.6}$$

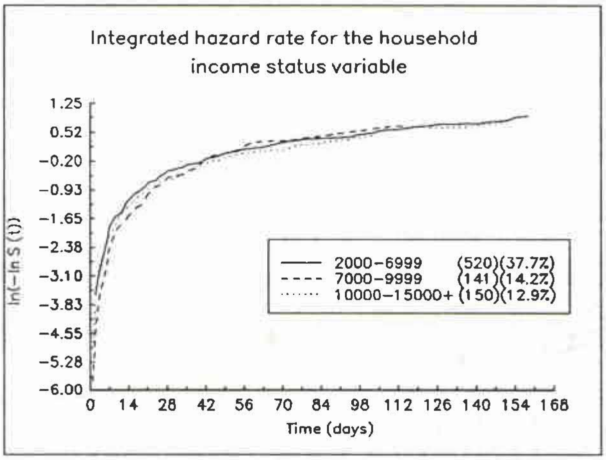
where $\mathbf{x}$ is a vector of covariates, i corresponds to the stratum of a variable with i=1,2,..,I, and β is the corresponding parameter vector. Once an estimate of β is obtained, the corresponding survivor functions, $\hat{S}_{0\mathrm{i}}(t)$, for each of the i strata can be estimated. The logarithm of the integrated hazard rate (ie. ln [$-$ln $\hat{S}_{0\mathrm{i}}(t)$]) can then be calculated for a specified value of $\mathbf{x}$, and when it is plotted against time for each of the i strata, a graphical check for proportionality between the curves can be conducted. If the resultant curves have approximately constant differences over time then the proportionality condition is assumed to hold and thus the variable defining the stratum may be incorporated as a covariate. If, on the other hand, the stratified integrated hazard curves do not result in proportional hazard rates, the factor being investigated should not be included as a covariate value. Kalbfleisch and Prentice (1980) suggest that such factors are more appropriately considered as stratification variables, ie. allowing them to define homogeneous subgroups within the data set and to then conduct all further analysis on these subgroups.

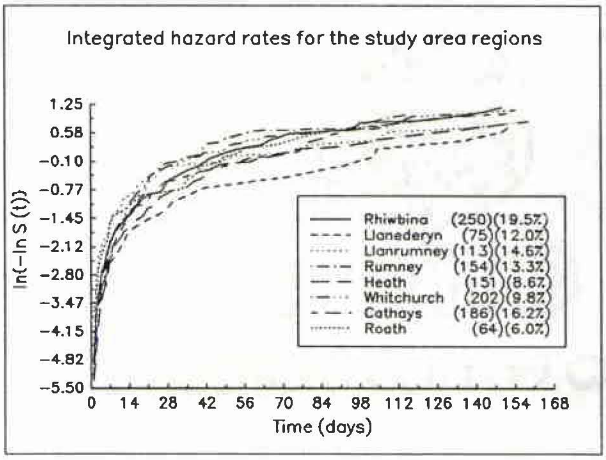
A stratified Cox model of the form given in equation (4.1.6) was used to determine if the length of residence (LOR) variable could be included as a covariate in this analysis. The 10 covariates which were identified in the initial phase of the exploratory analysis as being proportional over time (namely, the number of interpurchases (NIP), deep freezer ownership (DFO), possession of a driver's license (LIC), age (AGE), marital status (MART), the presence of young children (YC), the presence of older children (OC), household size (HSZ), the panellist's *perceived* frequency of weekly shop visits (FREQ), and accessibility to district stores (ADS)) were included as covariates in equation (4.1.6) and the length of residence (LOR) variable was allowed to define the stratum with base–line hazard $h_{0i}(t)$, where i=1,2,3. The corresponding survivor function estimates, $\hat{S}_{0i}(t)$, were calculated and the integrated survival rates ie., $\ln[-\ln \hat{S}_{0i}(t)]$ were plotted against time for each i. The resulting curves, shown in Figure 4.1.2 (page 194), are seen to have approximately constant differences over time. This suggests that the assumption of proportionality holds for this variable and that the relationship between survival and length of residence (LOR) illustrated in Figure 4.1.1 is indeed the manner in which length of residence (LOR) influences duration times. Therefore, length of residence (LOR) was incorporated as a covariate in the remainder of this analysis. Moreover, because no 'natural' order to incremental increases in length of residence (LOR) with survival occurs, dummy variables were created which reflect the effect of length of residence (LOR) on the baseline hazard rate. This was achieved by using the length of residence (LOR) category of 0 to 3 years as the base category and including two dummy variables to represent lengths of residence of 3 to 10 years (ie. LOR1) and 10 or more years (ie. LOR2).

The same format used to examine length of residence (LOR) was employed for evaluating the influence of income status (INC) on the duration times between store switches and the resultant curves of the integrated hazard rate estimates are given in Figure 4.1.2. While only slight differences between strata occur for the income status (INC) variable, these differences are approximately constant over time, suggesting that the proportionality assumption for income status holds. Income status (INC) can therefore be represented as a covariate in the analysis, but since the income status (INC) categories also do not correspond to a 'natural' order with regard to survival, income status (INC) is incorporated into the baseline

Figure 4.1.2: Integrated hazard rate curves for stratified Cox model estimates for the length of residence (LOR), income status (INC) and study area variables. Curves are standardized to categories NIP=3, DFO=0, LIC=0, AGE=2, MART=1, HSZ=2, YC=0, OC=1, FREQ=2, ADS=0, LOR=2, INC=1.







(note: numbers in parentheses refer to the number of observations in the study study data set whilst percentages in parentheses reflect the corresponding percentages in the Cardiff Consumer Panel) hazard rate with income levels in the £7000 to £9999 range defining the base category and including two dummy variables to represent incomes of £2000 to £6999 (ie. INC1) and incomes of £10000 or more (ie. INC2).

The possible influence of study area on survival was also investigated using a stratified Cox model and in this estimation the length of residence (LOR) and income status (INC) variables were added to the set of covariates in equation (4.1.6), with the eight study areas defining the stratum. The resultant plots of the logarithm of the integrated hazard rate are shown in Figure 4.1.2. While some of the curves exhibit proportional differences, such as those representing Rhiwbina, Llanederyn, Rumney and Heath, others, for example, Cathays and Roath, do not appear to have constant separation and thus may deviate from the proportionality assumption of Cox's model. Therefore, some regional differences are apparent but their overall effect on the hazard rate does not appear to be consistent. It was decided to include the possible influences of study areas by incorporating seven dummy variables in the remainder of the analysis, with Roath defining the base category.

The results from the exploratory analysis lead to a tentative model for the hazard rate of the duration data which can be written as:

$$\hat{h}(t;\mathbf{x};j;k) = h_0(t)\exp\beta(\mathbf{x}+\ \varphi_j+\ \xi_j+\ \rho_j+\ \zeta_k), \qquad (4.1.7)$$

$$(j = 1,\ldots,3) \text{ and } (k = 1,\ldots,8)$$

where β is a parameter vector for the covariates. The vector of covariates in $\mathbf{x}$ includes deep freezer ownership (DFO), possession of a driver's license (LIC), marital status (MART), young children (YC), older children (OC), the accessibility to district stores (ADS), the number of interpurchases (NIP), the panellist's age (AGE), and the household size (HSZ). Dummy covariates are used to represent the length of residence (LOR) variable (with φ_1=0), the frequency of weekly shopping trips (FREQ) variable (with ξ_1=0), the income status (INC) variable (with ρ_2=0) and the influence of the study areas (with ζ_8=0).

4.2 Event History Modelling

This stage of the analysis considers the distributional form of duration dependence using an event history modelling approach. Recall that the store choice behaviour being investigated in this research concerns a model in which panellists are assumed to occupy only two states, either shopping at a district centre store or shopping at a local centre store. The duration between store switches corresponds to the length of time a panellist remains loyal to one particular store type, ie. district or local. In the terminology of Section 2.5, this 'duration in state' can be thought of in terms of a 'hazard rate' in which the duration until a store switch/event occurs (ie. a change in state) is a function of the length of time since the store type was last chosen (ie. the time spent in that state). The probability of switching store types at a given point in time is then conditional upon not yet having switched store types and the distributional form of the hazard rate indicates the way in which duration dependence influences store switching behaviour.

Initial description of duration dependence was confined to evaluating alternative distributional forms of the hazard rate without considering the influence of covariates. This initial evaluation considered the appropriateness of the parametric specifications of the exponential, Weibull, Gompertz, log–normal and log–logistic distributions in representing the observed durations. Essentially, these alternative parametric forms for 'time until event occurrence' or durations, T, were specified and the relative fit of these different event history models to the observed durations was assessed in terms of the log–likelihood estimates.

Recall from Section 2.5.4 that the exponential model is a one parameter distribution which assumes that the hazard rate is independent of duration, that is,

$$\hat{h}(t) = \lambda \tag{4.2.1}$$

where λ is a constant value reflecting the location parameter. The Weibull model is a two parameter model which specifies a power dependence of the hazard rate on duration, ie.:

$$\hat{h}(t) = \lambda\alpha(\lambda t)^{\alpha-1}, \qquad (4.2.2)$$

where λ corresponds to the location parameter and a is a shape parameter, with $\lambda > 0$ and $a > 0$, whilst if $a=1$ the Weibull model simplifies to the exponential model. The Gompertz model is also a two parameter model with hazard rate:

$$\hat{h}(t) = \lambda_0\exp(\delta t)\ , \qquad (4.2.3)$$

where $\lambda_0 > 0$ represents the hazard rate at duration zero and $-\infty < \delta < \infty$ is the shape parameter of the distribution. The exponential, Weibull and Gompertz models are all monotonic functions whereas both the log–normal and log–logistic allow for the hazard rate to change direction with duration. The log–normal distribution resembles a positively skewed normal distribution with a hazard rate of:

$$\hat{h}(t)=(2\pi)^{-0.5}at^{-1}\exp[0.5\{-\alpha^2(\ln\lambda t)^2\}]/\{1-\phi(a\ln\lambda t)\} \qquad (4.2.4)$$

where ϕ is the distribution function of the standard normal distribution, $a>0$ is a shape parameter and $\lambda>0$ corresponds to a scale parameter. In the log–normal model, the hazard rate has a value of 0 at $t=0$, increases to a maximum and then decreases, approaching zero as t increases. Alternatively, the log–logistic model approximates the log–normal model and is computationally more convenient for censored data. The log–logistic hazard rate can be expressed as:

$$\hat{h}(t) = \lambda a(\lambda t)^{a-1}\ /\ \{1+(\lambda t)^{\alpha}\} \qquad (4.2.5)$$

with λ and $\alpha > 0$. λ corresponds to the location parameter of the hazard distribution and α reflects the shape parameter. When $a>0$ the log–logistic hazard rate resembles that of the log–normal hazard rate and when $\alpha<1$ the log–logistic has a monotone decreasing hazard from $+\infty$.

These five parametric models were used to estimate the hazard rates for the duration data. An output error was discovered in the main software package used in this analysis (ie. LIMDEP) in which the starting values needed for estimating the Gompertz model could not be acquired from the KM survival estimates. Furthermore, LIMDEP did not allow starting values to be specified directly for Gompertz model estimation. Consequently, the Gompertz model was estimated by programming in the log–likelihood equation directly and then minimizing the log–likelihood function using a quasi–Newtonian algorithm. This was achieved using the MINIMIZE utility in LIMDEP[3]. The estimated parameters and the associated log–likelihoods[4] which were derived for each of the five parametric models are given in Table 4.2.1 (page 199) and the corresponding estimated hazard rate curves are illustrated in Figure 4.2.1 (page 199).

The log–likelihood values given in Table 4.2.1 indicate that a Gompertz distribution with parameters λ_0=–0.029 and δ=0.037 provides the best fit to the durations. Conversely, the exponential model is seen to give the worst fit to the durations which indicates that the constant hazard rate assumption is least appropriate for this data which, in turn, implies that duration dependence does exist. With the exception of the exponential model, all of the hazard rates illustrated in Figure 4.2.1 decrease with increasing duration, ie. they exhibit negative duration dependence. It is important to note that the vast majority of the observations are concentrated in the shorter durations. For example, almost 30% of

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[3]This was preformed by Dr. Reader

[4]The exponential, Weibull and log–logistic model parameter estimates were derived from LIMDEP using the Davidon, Fletcher and Powell (DFP) algorithm (see Gruvaeus & Joreskog, 1970) and the log–normal parameters were derived in LIMDEP using a quasi–Newtonian algorithm (see Berndt et al., 1974; Gruvaeus & Joreskog, 1970). These models were all estimated using the custom survival model routines within LIMDEP which are based on using the log of duration as the 'dependent variable'. The procedure outlined above for the Gompertz model estimation, however, uses duration directly. This has the effect of producing log–likelihood values on a different scale to those produced from the custom routines. Therefore, to achieve consistency in reporting log–likelihood, the log–likelihoods of the exponential, Weibull, log–normal and log–logistic were all re–calculated, for each model application, using the MINIMIZE utility. This again, was preformed by Dr. Reader.

Table 4.2.1: Model parameter estimates for *all* durations

Regressor Variable	Model Parameter Estimates				
	Exponential	Weibull	Gompertz	Log-normal	Log-logistic
$\alpha/[\delta]$	1.000	0.576	[-0.029]	0.496	0.812
$\lambda/[\lambda_0]$	0.012	0.012	[0.037]	0.028	0.031
Log-likelihood	-4182.2	-3962.8	-3843.2	-3865.0	-3889.8

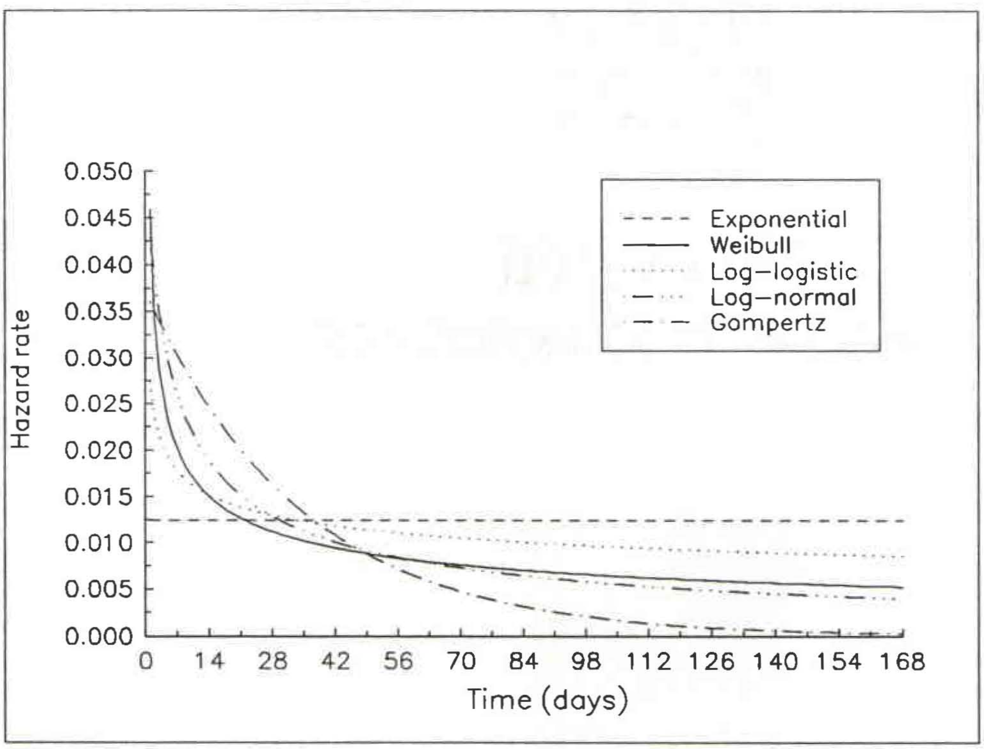


Figure 4.2.1: Estimated hazard rate curves for *all* durations

the durations have duration lengths of 7 days or less, over 50% of the durations are for 21 days or less and close to 70% of the durations are associated with duration lengths of 56 days or less (see Figure B.2, Appendix B). Consequently, relatively fewer observations are defining the hazards in the longer durations.

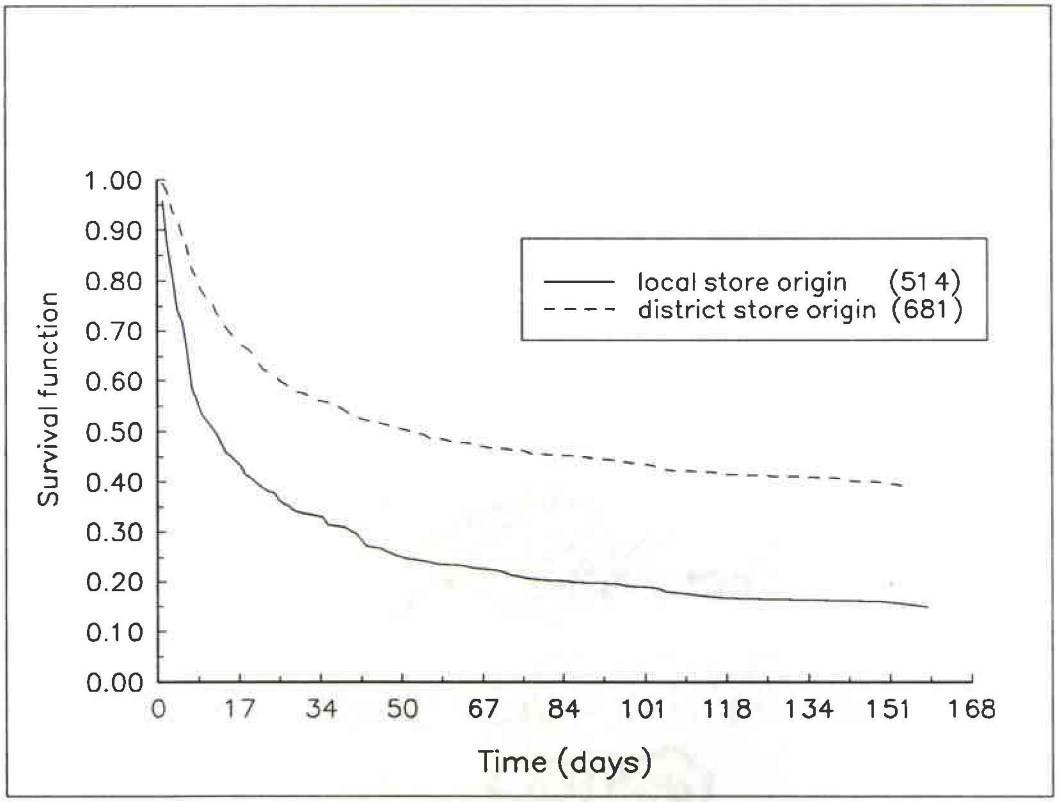
Figure 4.2.1 shows that, in the smaller durations, the log–logistic, Weibull and log–normal models all have more rapid declining hazard rates relative to that of the Gompertz model. The log–logistic and the Weibull models sharply decrease in the shorter durations (ie. those less than about 14 days) and the log–normal decreases slightly less sharply to longer durations (ie. durations of approximately 30 days), after which time all three models exhibit relatively small changes in the hazard rate. The Gompertz model is distinctive from the other models by exhibiting smaller rates of change in the hazard in the shorter durations, with a 'bottoming out' in the rate of decline at longer durations, ie. those longer than about 56 days. It is possible that the Gompertz model is underestimating the hazard rate in the longer durations due to the fact that the Gompertz is constrained to approach zero (see Kalbfleisch & Prentice, 1980) and certainly the log–normal, log–logistic and Weibull models all indicate higher absolute hazard rates in the longer durations. However, since fewer durations are defining the tails of the distributions, the Gompertz still comes out as giving the best overall fit to this data.

The estimated hazard rate curves described above consider *all* durations regardless of store type. However, it may be that the durations associated with the district centre store–type differ from those associated with the local centre store–type. Recall from Section 4.1 that stratified Kaplan–Meier survival estimates can be used to determine if the probability of experiencing an event is specific to a covariate. Therefore, in order to determine if the durations associated with local store shopping were inherently different than the durations corresponding to district store shopping, a binary covariate representing the type of store (ie. STYP) at the beginning of each duration was created. In event–history modelling terms, this store type (STYP) variable essentially represents the *state* of the durations. This store type (STYP) variable was then used to stratify the durations and the corresponding KM survival estimates, ie. $\hat{S}(t_j;\mathbf{x}_i)$ where i=2, were calculated. These KM estimated survival rates were plotted over time to derive survival curves representing the differences in survivorship associated with local and district store durations. The resultant survival curves are illustrated in Figure 4.2.2 (page 202).

From Figure 4.2.2, it is apparent that the durations observed for the district store–type possess higher survival rates than those corresponding to the local store–type. This, in turn, implies that shopping at the district centre store–type tends to lead to longer durations of habitual choice of the district centre stores than does shopping at the local centre store–type. In other words, district store shopping appears to be associated with longer durations of 'loyalty' compared to the durations of 'loyalty' towards local stores. Therefore, it is concluded that the *state* of the duration is likely an important influence on store choice behaviour. Given this, the variable representing store type (STYP) was used to disaggregate the durations and the exponential, Weibull, Gompertz, log–normal and log–logistic distribution parameters were derived separately for the local and district store durations and the corresponding estimated hazard rate curves were also produced.

The parameter estimates for the local store durations are given in Table 4.2.2 (page 204), those for the district store durations are listed in Table 4.2.3 (page 205) and the corresponding hazard rate curves are illustrated in Figure 4.2.3 (page 204) and Figure 4.2.4 (page 205), respectively. In Tables 4.2.2 and 4.2.3, the exponential model is seen to provide the worst fit to both the local and district store durations which implies that duration dependence exists in both local and district store choice behaviour. A log–normal model with α=0.584 and λ=0.062 is seen to give the best fit to the local store durations whilst a Gompertz model with δ=–0.026 and

Figure 4.2.2: **Estimated KM survival curves for the durations† stratified by the store type (STYP) variable**



† estimates are based on the original 1,195 durations (see Section 3.3.2)

λ_0=0.024 is seen to best represent the district store durations. These findings imply that the form of duration dependence associated with the local store durations is different from the duration dependence associated with the district store durations.

The estimated hazard rates curves for the local store durations shown in Figure 4.2.3, indicate that in the longer durations (ie. those longer than approximately 45 days) the log–normal and the log–logistic distributions are very similar in terms of the changes in value of the hazard rate. The log–normal is distinguished from the log–logistic, for durations of about 5 to 45 days, exhibiting relatively smaller values in the hazard rate. The Gompertz distribution, on the other hand, is seen to possess smaller rates of change in the hazard in the very short durations (ie. those less than about day 4) than estimated in either the log–normal or the log–logistic models which may be, at least in part, governed by the smaller value of the Gompertz hazard at time 0. Alternatively, the Weibull distribution exhibits the steepest decline in the hazard rate in the shorter durations (ie. those less than approximately 14 days), after which time the Weibull hazard decreases more gradually over longer durations.

As illustrated in Figure 4.2.4, both the log–normal and log–logistic estimated hazard rate curves for the district store durations are seen to be approximately identical. The form of the hazard distribution of the Weibull model approximates both the log–normal and the log–logistic models after durations of approximately 66 days, but the Weibull exhibits a more rapidly declining hazard rate in the earlier durations than either of these other two models. Alternatively, the Gompertz model possesses a more gradual decline in the hazard rate in the shorter durations, up to durations of approximately 14 days. After the durations of about 14 days, the Gompertz hazard declines even more gradually but at a higher rate than the other models up to durations of approximately 120 days, after which time little change in the Gompertz hazard is observed.

Table 4.2.2: Model parameter estimates for the local store durations

Regressor Variable	Model Parameter Estimates				
	Exponential	Weibull	Gompertz	Log-normal	Log-logistic
$\alpha/[\delta]$	1.000	0.615	[-0.031]	0.584	0.978
$\lambda/[\lambda_0]$	0.023	0.028	[0.059]	0.062	0.069
Log-likelihood	-1892.7	-1794.6	-1741.3	-1737.5	-1744.1

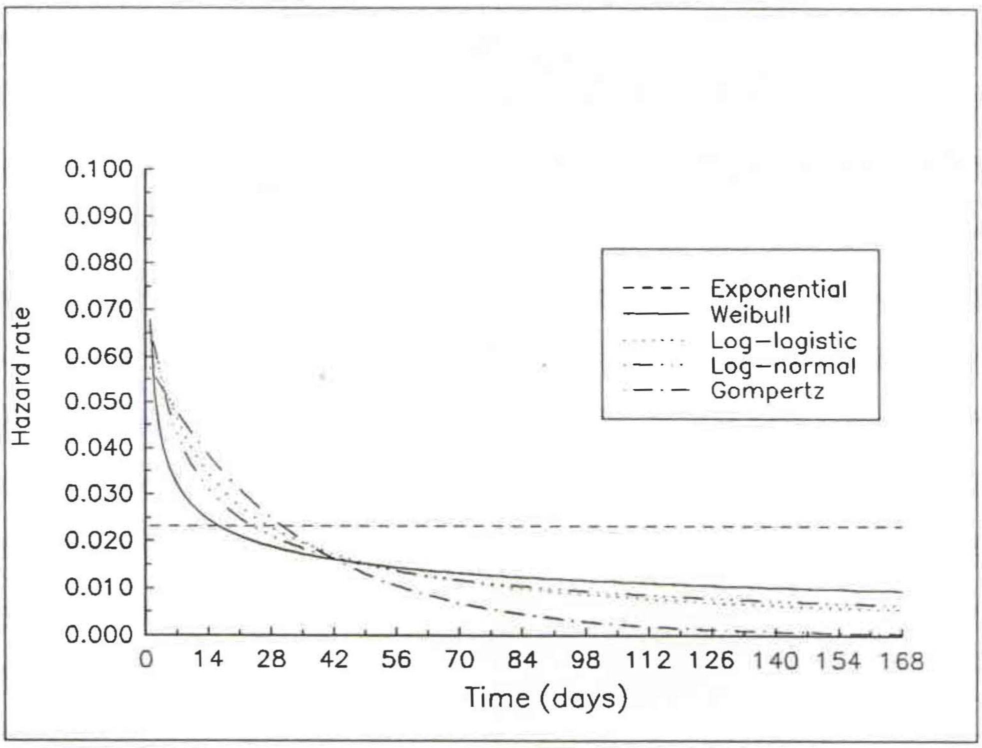


Figure 4.2.3: Estimated hazard rate curves for the local store durations

Table 4.2.3: Model parameter estimates for the district store durations

Regressor Variable	Model Parameter Estimates				
	Exponential	Weibull	Gompertz	Log-normal	Log-logistic
$\alpha/[\delta]$	1.000	0.595	[-0.026]	0.478	0.779
$\lambda/[\lambda_0]$	0.008	0.007	[0.024]	0.015	0.016
Log-likelihood	-2192.5	-2105.5	-2044.9	-2062.1	-2077.8

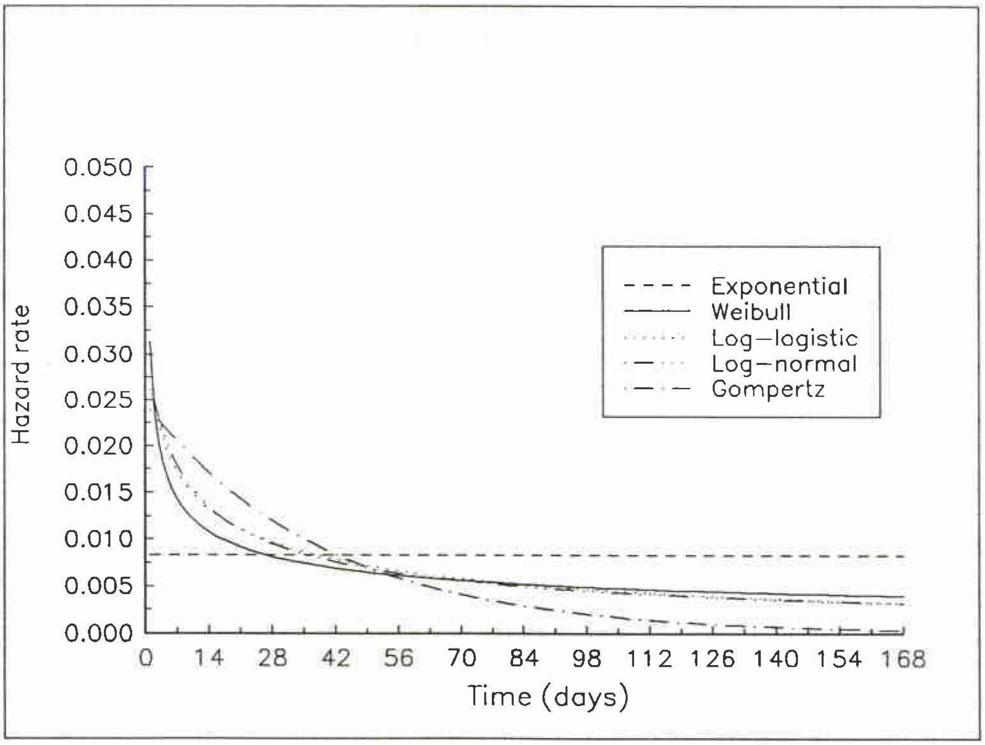


Figure 4.2.4: Estimated hazard rate curves for the district store durations

A comparison of Figure 4.2.3 with Figure 4.2.4 reveals that the absolute values of the estimated hazards for the local store durations are approximately (or more than) twice as large in the smaller durations (ie. those less than or equal to day 56) than the hazard rates for the district store durations over the same duration lengths. For example, for durations of about 56 days, the log–normal model has a hazard rate of $\hat{h}(t)$=0.014 for local store durations whilst the Gompertz model has a hazard rate of $\hat{h}(t)$=0.007 for the district store durations. Given that the vast majority of the observed durations are associated with these shorter duration lengths (see Figure B.2, Appendix B), these differences between the local and district store hazard rates indicate that the hazard of switching from a local store to a district store is approximately twice as large as the hazard of switching from a district store to a local store. Therefore, it is possible that the log–normal provides a better fit to the local store durations than the Gompertz model because the log–normal model is more flexible in the shorter durations, and shorter durations are likely more important in local store choice behaviour. On the other hand, the district store durations may be better represented by the Gompertz than either the log–normal or log–logistic models since both the log–normal and log–logistic estimate relatively higher rates of change in hazard in the earlier durations than the Gompertz, and longer durations likely to be more important in district store choice behaviour. Furthermore, when the estimated hazard rates of the local and district store durations are compared to the durations in which no distinction is made between the two store types (see Figure 4.2.1) it appears, not surprisingly, that for *all* durations the hazard rates reflect an average of the local and district store hazard rates.

4.3 Event History Regression Modelling

Thus far the investigation of duration dependence has not considered the influence of exogenous covariates on duration and it is to this issue that we now turn. Examination of the effects of covariates on duration was initially restricted to the covariates representing the length of residence (LOR), deep freezer ownership (DFO), possession of a driver's license (LIC), age of the panellist (AGE), marital status (MART), household size (HSZ), the presence of both young children (YC) and older children (OC), the *perceived* frequency of weekly shopping (FREQ), accessibility to district stores (ADS), and those representing the study areas. Furthermore, the variable representing the type of store (ie. STYP) at the beginning of each duration was added to this list of covariates. The covariates are included in the models as specified in equation (4.1.7), with store type (STYP) included in the covariate vector, $\mathbf{x}$.

The influence of covariates on duration can be examined by including them into the parametric forms previously investigated or alternatively, they can be examined using Cox's (1972) proportional hazards model in which there is no parametric specification of the baseline hazard rate. Recall from Section 2.5.6 that Cox's proportional hazards model assumes that the ratio of the hazards for any two individuals with covariates x_1 and x_2 is proportional. The hazard rate of Cox's proportional hazards model can be written as:

$$h(t;\mathbf{x}) = \lambda_0(t) \exp(\mathbf{x}\boldsymbol{\beta}) , \qquad (4.3.1)$$

where $\lambda_0(t)$ represents the (unspecified) baseline hazard rate, $\mathbf{x}$ is a vector of covariates and $\boldsymbol{\beta}$ is the corresponding parameter vector. As mentioned in Section 4.1, equation (4.3.1) can also be extended to allow for different baseline hazards for subsets of the data. Based on the estimated hazard rate curves obtained for the local and district store durations (Figures 4.2.3 and 4.2.4, respectively) it is possible that the baseline hazard rate associated with the local store durations is different from the baseline hazard associated with the district store durations. Cox's proportional hazards model stratified by the store type variable (STYP) may be written as:

$$\hat{h}_i(t;\mathbf{x}) = \lambda_{0i}(t)\exp(\mathbf{x}\boldsymbol{\beta}) \; , \qquad (4.3.2)$$

where i=1 corresponds to the local store durations and i=2 reflects the district store durations.

Parameter estimates were derived for *all* durations using both Cox's proportional hazards model, equation (4.3.1) as well as the stratified Cox model, equation (4.3.2), in order to gain insight as to whether different baseline hazard rates exist and to evaluate the influence of the covariates on the hazard rate. The influence of the exogenous covariates on duration was also investigated using the exponential, Weibull, Gompertz, log–normal and log–logistic models. Covariates were included in these models by extending λ to $\lambda\exp(\mathbf{x}\boldsymbol{\beta})$, where $\mathbf{x}$ is a vector of covariates and $\boldsymbol{\beta}$ is the corresponding parameter vector. The parameter estimates derived from these models along with their estimated log–likelihoods are listed in Table 4.3.1 (page 209) and the estimated hazard rate curves calculated at the means of the covariates are illustrated in Figure 4.3.1 (page 210).

A comparison of the log–likelihood estimates for the Cox model (ie. $\mathscr{L}=-4932.5$) with that of the stratified Cox model ($\mathscr{L}=-4375.6$) indicates that the stratified Cox model provides a better representation of the durations (see Table 4.3.1). The corresponding likelihood ratio gives a $\chi^2=1113.8$ with 1 degree of freedom which indicates that this improvement in fit is significant at the 99.9% confidence level. These findings suggest that the baseline hazard of the local store durations is different from the baseline hazard of the district store durations. This, in turn, implies that the duration dependence associated with local store choice may be different from that of district store choice when the behavioural variation due to population heterogeneity is included in model estimates.

Table 4.3.1: Model parameter estimates of *all* durations including the influence of exogenous covariates

Regressor Variable	Model Parameter Estimates						
	Cox	Cox‡	Exponential	Weibull	Gompertz	Log-normal	Log-logistic
constant	-	-	3.219 (0.241)	2.878 (0.455)	2.505 (0.333)	2.170 (0.486)	2.081 (0.469)
DFO	0.260** (0.082)	0.298** (0.082)	0.313** (0.057)	0.391** (0.109)	0.264** (0.077)	0.372** (0.118)	0.420** (0.116)
LIC	0.291** (0.102)	0.269** (1.00)	0.319** (0.081)	0.427** (0.152)	0.296** (0.108)	0.539** (0.163)	0.553** (0.154)
AGE	0.233** (0.047)	0.211** (0.047)	0.335** (0.036)	0.398** (0.067)	0.246** (0.047)	0.271** (0.066)	0.298** (0.064)
MART	-0.056 (0.114)	-0.014 (0.114)	0.022 (0.092)	-0.010 (0.170)	-0.044 (0.119)	-0.047 (0.173)	-0.070 (0.167)
YC	0.130 (0.098)	0.143 (0.099)	0.184** (0.067)	0.187 (0.132)	0.123 (0.095)	0.159 (0.159)	0.181 (0.155)
OC	0.139 (0.107)	0.015 (0.106)	-0.008 (0.080)	-0.015 (0.147)	0.022 (0.105)	0.046 (0.156)	0.071 (0.151)
HSZ	-0.144** (0.037)	-0.152** (0.037)	-0.173** (0.027)	-0.218** (0.053)	-0.151** (0.037)	-0.257** (0.060)	-0.286** (0.058)
ADS	0.641** (0.161)	0.867** (157)	1.004** (0.117)	1.225** (0.224)	0.679** (0.155)	1.008** (0.229)	1.134** (0.227)
LOR1	-0.131 (0.115)	-0.068 (0.116)	-0.264** (0.070)	-0.241 (0.140)	-0.148 (0.101)	0.025 (0.165)	0.040 (0.163)
LOR2	0.230 (0.129)	0.048 (0.129)	-0.035 (0.089)	-0.018 (0.171)	0.008 (0.125)	0.280 (0.189)	0.241 (0.185)
FREQ1	0.037 (0.094)	0.104 (0.094)	0.023 (0.069)	0.090 (0.130)	0.046 (0.091)	0.201 (0.140)	0.246 (0.137)
FREQ2	0.076 (0.095)	0.117 (0.095)	0.031 (0.063)	0.112 (0.123)	0.071 (0.089)	0.300* (0.145)	0.318* (0.142)
Rhiwbina	-0.121 (0.189)	-0.282 (0.188)	-0.327* (0.132)	-0.318 (0.243)	-0.130 (0.180)	-0.230 (0.258)	-0.237 (0.254)
Llanederyn	0.890** (0.270)	0.872** (0.270)	1.022** (0.223)	1.409** (0.390)	0.901** (0.279)	1.390** (0.353)	1.504** (0.356)
Llanrumney	-0.011 (0.270)	-0.243 (0.269)	-0.249 (0.205)	-0.202 (0.366)	-0.422 (0.266)	-0.054 (0.362)	-0.059 (0.359)
Rumney	-0.047 (0.216)	-0.274 (0.214)	-0.333* (0.152)	-0.276 (0.286)	-0.068 (0.212)	-0.075 (0.311)	-0.019 (0.305)
Heath	0.170 (0.214)	-0.143 (0.210)	0.050 (0.147)	0.150 (0.275)	0.164 (0.204)	0.237 (0.305)	0.243 (0.299)
Whitchurch	-0.071 (0.208)	-0.323 (0.206)	-0.237 (0.144)	-0.177 (0.270)	-0.094 (0.198)	-0.008 (0.304)	-0.024 (0.297)
Cathays	-0.158 (0.225)	-0.400 (0.222)	-0.430** (0.156)	-0.444 (0.293)	-0.189 (0.216)	-0.258 (0.329)	-0.295 (0.321)
STYP	0.610** (0.080)	-	0.739** (0.058)	0.956** (0.110)	0.621** (0.076)	1.084** (0.110)	1.095** (0.108)
$\alpha/[\delta]$	-	-	1.000	0.670	[-0.024]	0.589	1.003
$\lambda/[\lambda_0]$	-	-	0.014	0.014	[0.034]	0.029	0.030
Log-likelihood	-4932.5†	4375.6†	-3900.6	-3776.5	-3675.5	-3691.7	-3701.0

* significant at the 95% level; ** significant at the 99% level
‡ model stratified on store type (local/district); † based on partial likelihood

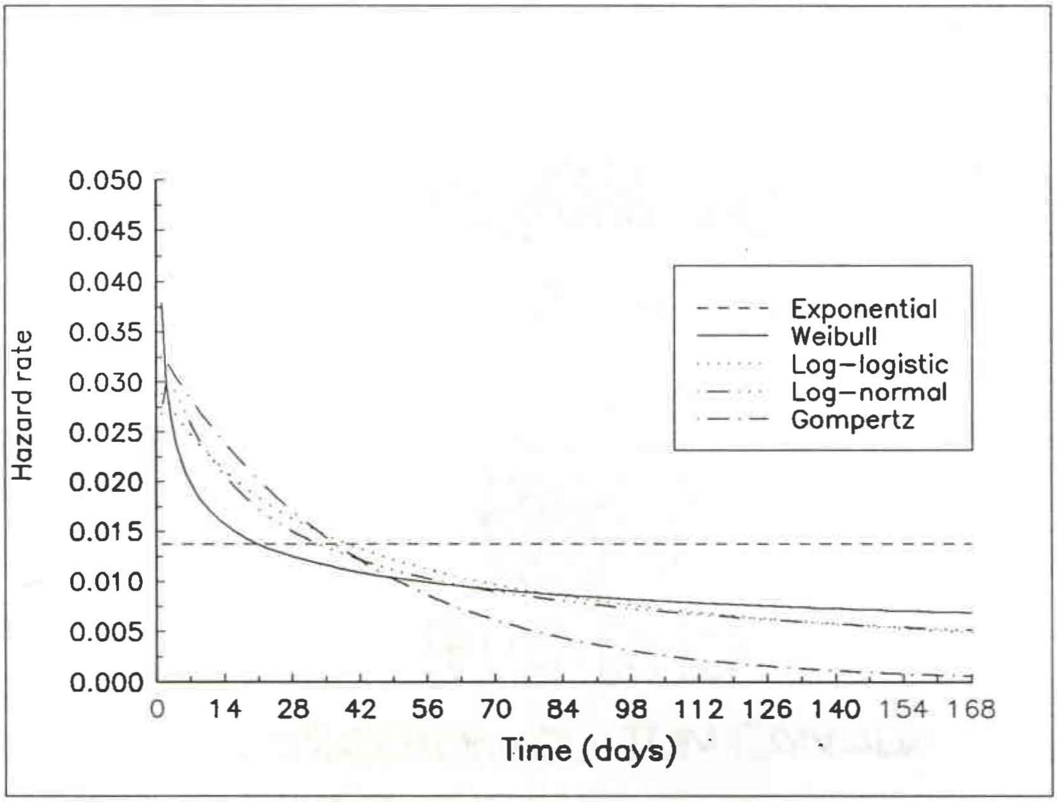


Figure 4.3.1: Hazard rate curves estimated at the mean of the exogenous covariates for *all* durations

The covariates estimated as significant in both the Cox model and the stratified Cox model reflect individual sources of behavioural variation which are important influences on duration. In both of these models the covariates representing deep freezer ownership (DFO), possession of a driver's license (LIC), the age of the panellist (AGE), household size (HSZ), accessibility to district centre stores (ADS), the Llanederyn study area and the store type variable (STYP) are all significant at the 99% level. It is interesting to note that the covariates estimated as significant in the Cox and stratified Cox models are also estimated as being significant in the five parametric models (see Table 4.3.1), which reinforces the notion that these particular covariates are important.

The estimated log–likelihoods for the parametric models indicate that a Gompertz model with δ=–0.024 and λ_0=0.034 best fits *all* durations ($\mathscr{L}$=–3675.5) whilst an exponential model with λ=0.014 gives the worst fit (see Table 4.3.1). The log–logistic and log–normal log–likelihoods are similar indicating that these two models give approximately the same fit to these durations. Recall from Table 4.2.1 that a Gompertz distribution was also found to best represent *all* durations ($\mathscr{L}$ =–3843.2) without covariates and this is perhaps not surprising, considering that the influence of covariates is to simply increase or decrease the hazard rate. For the Gompertz model, a likelihood ratio test of the null hypothesis H_0: β=0, gives a χ^2=365.4 with 19 degrees of freedom which indicates that the null hypothesis of no influence of the covariates on the durations can be rejected at the 99.9% confidence level.

From the estimated hazard rate curves shown in Figure 4.3.1, it is apparent that all of the models (except of course, the exponential model) largely exhibit negative duration dependence, ie. a decreasing hazard rate. The log–normal model estimates slightly smaller values of the hazard than the log–logistic at the beginning of the study period, but then increases to a maximum value by durations of about 3 days and then decreases thereafter. The log–logistic model, on the other hand, decreases from its initial maximum value of 0.029 and approximates the log–normal over longer durations (ie. those greater than approximately 98 days). The Weibull model exhibits the steepest decline in the hazard rate for durations of less than 7 days, after which time the rate of change in the Weibull hazard gradually decreases. Alternatively, the Gompertz model initially exhibits a smaller absolute value in the hazard than the Weibull, but for durations of approximately 3 to 30 days, the Gompertz exhibits higher absolute values of the hazard rate with duration than any of the other models and maintains a gradually decreasing hazard rate over all durations, approaching zero as duration increases.

In addition to the covariates identified above as significant in the all of the models estimated, the exponential model estimates the covariates representing the presence of young children (YC), lengths of residence of 3 to 10 years (LOR1) and living in Rhiwbina, Rumney and Cathays as significantly influencing *all* durations. These findings may simply reflect the constant hazard rate specification of the exponential model. Essentially, behavioural variation due to duration dependence may be attributed to these covariates since the durations are assumed to be independent of time and thus these covariates may be estimated as significant when, in fact, they may not be significant influences on the durations. Hence, when duration dependence is examined directly, (ie. the hazard rate is allowed to vary with time), the time–dependent behavioural variation associated with these covariates is included in the hazard rate estimates and thus these covariates are not seen to be significant. In other words, it is possible that these findings reflect the problem of 'spurious' heterogeneity (see Section 2.4.2) which may result from the exponential's time–independent hazard rate when a time dependent hazard rate actually exists.

In terms of those covariates which appear significant across all models, owning a deep freezer (DFO) is seen to positively influence duration or equivalently, decrease the hazard rate between store–type switches. This may result from a tendency for larger inventory purchasing by households which own a deep freezer so that such households may make fewer shopping trips (and hence possess lower purchasing frequencies) which may increase the duration between successive store trips. Furthermore, deep freezer ownership may encourage loyalty towards district centre stores as district stores are more likely to carry larger stocks than local stores and hence, fewer switches between district and local stores may occur which, in turn, could lead to longer durations between store–type switches. Possession of a driver's license (LIC) is also seen to positively influence the duration between store–type switches. It has been hypothesized that possessing a driver's license may decrease the overall number of shopping trips by encouraging larger amounts of inventory stocks to be purchased on any one store visit which, consequently, may result in longer durations between successive store trips. Moreover, having a driver's license may increase the duration between store switches by encouraging trips to store which offer items in bulk or which possess adequate parking facilities, ie. district center stores. Furthermore, the covariate representing the panellist's age (AGE) has a positive influence on the durations, reflecting longer durations between store–type switches with increasing age. The previously discussed greater mobility constraints and/or time constraints which may be associated with increasing age could result in fewer overall shopping trips which may tend to favor nearby stores, leading to longer durations between store trips. Alternatively, more habitual choice of closer stores has also been reasoned to occur for the older panellists and thus may explain the longer durations between store switches with increasing age.

Table 4.3.1 indicates that household size (HSZ) has a negative effect on the durations between store–type switches (ie. increases the hazard rate). This may be a result of higher consumption levels which have been associated with larger households and which may promote more frequent purchasing, thereby tending to decrease the duration between successive shopping trips. While larger households have been hypothesized to tend towards habitual store choice behaviour, in particular, 'loyalty' towards district stores, larger households may also be more likely to frequently switch between store types than smaller households, supplementing district store purchases with frequent visits to local stores, in order to maintain adequate stocks to meet the anticipated higher consumption levels.

Good accessibility to district centres (ADS) is seen to increase the duration between store switches which may result from lower switching rates for those households with good access to district stores. Essentially, it can be hypothesized that households with good accessibility to district stores use these stores *as if* they were local stores, 'topping up' inventory levels with purchases at district stores, which may mean that the majority of shopping trips for households with good access would be to district stores. Given this, it is perhaps not surprising that Llanederyn is estimated as significantly increasing duration. Llanederyn is different from the other study areas in that it has very little unplanned retailing and, from Table 3.1.1 (page 146), Llanederyn is the only study area which has good accessibility to district stores and poor accessibility to local stores. Therefore, the panellists in Llanederyn may tend to visit district stores for all their purchasing needs since local stores are not readily accessible which consequently, could result in longer durations between store switches.

The covariate representing store type (STYP) is estimated as significantly increasing duration which implies that district store shopping leads to longer durations of habitual store choice (ie. smaller hazard rates) relative to those associated with local store choice behaviour. It is also possible that trips to district stores may be associated with larger inventory purchasing on any one occasion, as district stores are likely to provide a greater variety of items, which may lead to lower purchasing rates for district store choice which, in turn, may result in smaller hazard rates for district store choice relative to that of local store choice. This finding provides further support for the notion that the duration dependence occurring in local store choice behaviour may be different from the duration dependence occurring in district store choice behaviour (see Section 4.2). Therefore, it is reasonable to suspect that the influence of individual sources of behavioural variation, as measured by the exogenous covariates, associated with the district store durations may be different from that associated with the local store durations. This hypothesis was investigated by disaggregating the durations according to store type and deriving estimates for the Cox, exponential, Weibull, Gompertz, log–normal and log–logistic models. Furthermore, the estimated hazard rates calculated at the mean of the covariates were plotted against duration to illustrate the influence of duration dependence on local and district store choice when covariates are included in model estimates. The resultant parameter estimates for the local store durations are listed in Table 4.3.2 (page 216) and those corresponding to the district store durations are given in Table 4.3.3 (page 221). Figure 4.3.2 (page 217) illustrates the hazard rate curve estimated at the mean of the covariates for the local store durations and Figure 4.3.3 (page 222) gives the curves corresponding to the district store durations.

From the log–likelihood estimates listed in Table 4.3.2 it appears as though a log–normal model, with α=0.698 and λ=0.062, provides a slightly better fit to the local store durations than a log–logistic model (with α=1.200 and λ=0.066). Conversely, the exponential and Weibull models are seen to give the worst fits to the local store durations. Recall from Section 2.5.5 that both the log–normal and the log–logistic models are accelerated failure–time models in which covariates have a multiplicative effect on duration. In other words, the influence of covariates is to alter (by accelerating or decelerating) the duration until a store–type switch (ie. an

Table 4.3.2: Model parameter estimates for the local store durations including the influence of exogenous covariates

Regressor Variable	Model Parameter Estimates					
	Cox	Exponential	Weibull	Gompertz	Log-normal	Log-logistic
constant	-	2.431 (0.441)	2.260 (0.073)	2.136 (0.572)	1.960 (0.658)	2.115 (0.699)
DFO	0.031 (0.117)	0.025 (0.861)	0.031 (0.146)	0.035 (0.114)	0.090 (0.154)	0.102 (0.151)
LIC	0.214 (0.165)	0.305* (0.153)	0.286 (0.246)	0.241 (0.178)	0.248 (0.208)	0.217 (0.218)
AGE	0.244** (0.070)	0.379** (0.053)	0.417* (0.092)	0.259** (0.073)	0.335** (0.092)	0.319** (0.092)
MART	-0.298 (0.162)	-0.372** (0.142)	-0.411 (0.237)	-0.299 (0.178)	-0.461* (0.212)	-0.549* (0.217)
YC	0.076 (0.140)	0.189 (0.105)	0.130 (0.179)	0.071 (0.135)	0.070 (0.193)	0.054 (0.199)
OC	-0.102 (0.140)	-0.189 (0.124)	-0.193 (0.204)	-0.113 (0.157)	-0.151 (0.196)	-0.106 (0.189)
HSZ	-0.095 (0.053)	-0.122** (0.046)	-0.136 (0.077)	-0.103 (0.059)	-0.157* (0.073)	-0.188* (0.076)
ADS	-0.683* (0.273)	-0.962** (0.196)	-0.941** (0.339)	-0.721** (0.265)	-0.814* (0.337)	-1.854* (0.368)
LOR1	-0.279 (0.165)	-0.489** (0.118)	-0.526** (0.204)	-0.309* (0.157)	-0.387 (0.227)	-0.322 (0.231)
LOR2	0.120 (0.193)	-0.004 (0.152)	0.037 (0.258)	0.106 (0.203)	0.177 (0.261)	0.301 (0.271)
FREQ1	-0.214 (0.134)	-0.351** (0.107)	-0.346 (0.179)	-0.221 (0.138)	-0.197 (0.172)	-0.159 (0.172)
FREQ2	-0.231 (0.138)	-0.354** (0.099)	-0.366* (0.163)	-0.260* (0.128)	-0.280 (0.179)	-0.264 (0.172)
Rhiwbina	0.713** (0.262)	1.046** (0.206)	1.131** (0.364)	0.747** (0.275)	0.901* (0.360)	0.798* (0.361)
Llanederyn	0.598 (0.413)	0.717 (0.376)	0.895 (0.644)	0.653 (0.461)	0.790 (0.555)	0.768 (0.565)
Llanrumney	1.043** (0.397)	1.512** (0.291)	1.536** (0.518)	1.090** (0.394)	1.232* (0.526)	1.139* (0.552)
Rumney	0.675* (0.323)	1.015** (0.268)	1.022* (0.460)	0.737* (0.348)	0.840* (0.428)	0.787 (0.434)
Heath	1.161** (0.320)	1.732** (0.269)	1.840** (0.458)	1.232** (0.347)	1.588** (0.415)	1.513** (0.424)
Whitchurch	0.911** (0.311)	1.484** (0.267)	1.538** (0.452)	0.959** (0.340)	1.218** (0.409)	1.085** (0.418)
Cathays	0.856* (0.353)	1.264** (0.284)	1.247** (0.484)	0.894* (0.372)	0.978* (0.447)	0.926* (0.469)
α/[δ]	-	1.000	0.031	[-0.024]	0.698	1.200
λ/[λ_0]	-	0.028	0.031	[0.056]	0.062	0.066
Log-likelihood	-2141.7†	-1743.8	-1703.4	-1661.3	-1654.6	-1657.5

* significant at the 95% level; ** significant at the 99% level

† based on partial likelihood

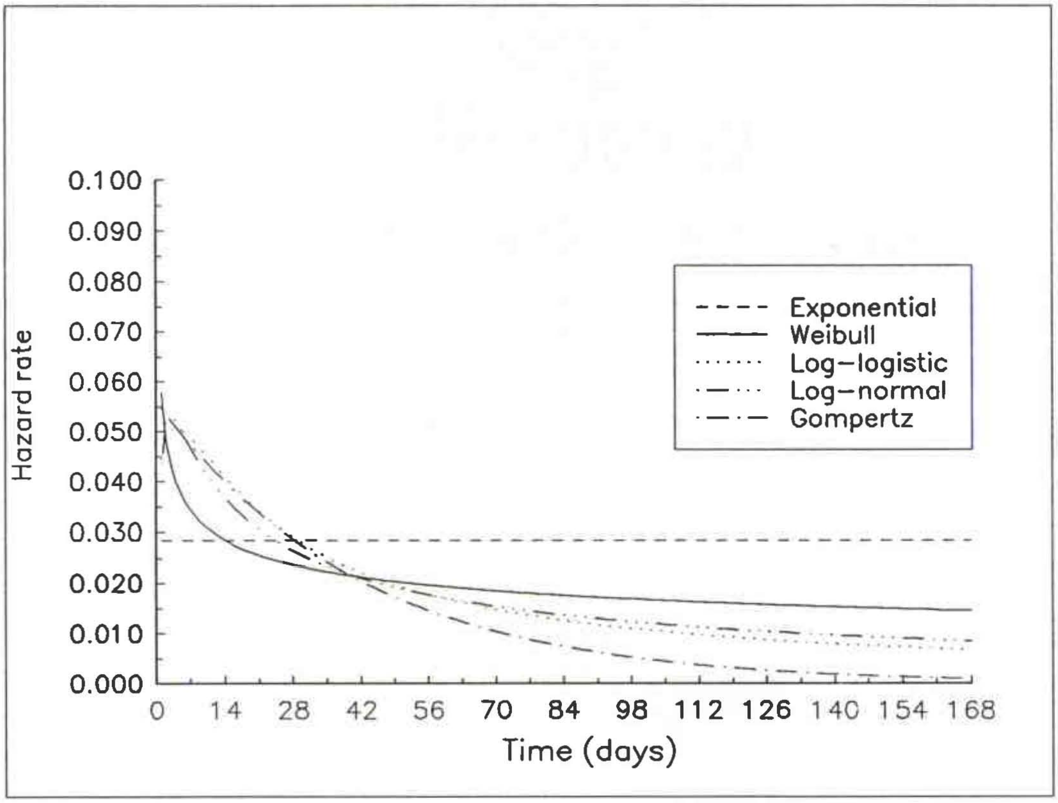


Figure 4.3.2: Hazard rate curves estimated at the mean of the exogenous covariates for the local store durations

event) occurs. Alternatively, the exponential and Weibull models are both accelerated failure–time models and proportional hazards models so that the multiplicative effect of covariates on duration is equivalent to their influence on the hazard rate. The log–normal and log–logistic models are distinctive from the exponential and Weibull (as well as the Gompertz model) in that they allow the hazard rate to change direction over time, ie. they are nonmonotonic functions.

The estimated hazard rate curves for both the log–normal and log–logistic models for the local store durations are seen to possess increasing hazard rates in the very short durations (ie. those less than approximately 4 days), after which time these hazards decrease with duration (see Figure 4.3.2). The log–normal hazard rate distribution is dissimilar from that of the log–logistic for durations of approximately 10 to 42 days, during which time the log–normal is seen to decrease more gradually with increasing duration. The log–logistic hazard rate appears to approximate the Gompertz hazard rate for durations of about 7 to 32 days, but then the log–logistic appears to decrease more gradually than the Gompertz until durations of approximately 140 days. The nonmonotonic distributional forms of both the log–logistic and log–normal models indicate that positive duration dependence is associated with very short durations (ie. those less than about 4 days) whilst negative duration dependence occurs for longer durations. This, in turn, means that very short durations of local store shopping are associated with an increasing hazard rate whereas local store shopping for longer durations is associated with a decreasing hazard rate.

Recall from Table 4.2.2 that the local store durations were best described by a log–normal distribution ($\mathscr{L}$=–1737.5) when covariates were not included and a log–normal distribution with $\mathscr{L}$=–1654.6 best fits the local store durations when covariates are included (Table 4.3.2). Evaluation of the null hypothesis, H_0:β=0, gives a χ^2=165.8 with 20 degrees of freedom and so the null hypothesis of no influence of the covariates on duration can be rejected at the 99.9% level. It is also interesting to note that the distributional form of the log–normal hazard rate derived for local store durations was monotonically decreasing when covariates were not included (see Figure 4.2.3), but when covariates are included, the estimated hazard rate, calculated at the mean of the covariates, possesses a nonmonotonic distributional form, exhibiting positive duration dependence in the very short durations (ie. those less than 4 days) and negative duration dependence in longer durations. This implies that the behavioural variation associated with very short local store durations may be different than the behavioural variation associated with longer durations of local store choice.

The covariates representing age (AGE) and accessibility to district stores (ADS) are seen to be significant to local store durations across all the models estimated (see Table 4.3.2). The age (AGE) covariate positively influences durations of local store choice which may reflect more habitual store choice behaviour of older panellists who may favor nearby stores and/or the less frequent purchasing behaviour hypothesized to occur with increasing age. For reasons stated earlier, it is perhaps not surprising that having good accessibility to district stores (ADS) is seen to decrease the duration spent shopping at local stores. This provides support for the notion that panellists with good accessibility to district stores will exhibit a greater mix of local and district store visits, resulting in higher hazard rates associated with switching from a local store to a district store. Table 4.3.2 also indicates that living in Rhiwbina, Rumney, Llanrumney, Heath, Whitchurch and Cathays leads to longer durations of habitual local store choice relative to the effect of living in Roath, the base category study area. This finding is perhaps not surprising given that Roath is associated with good accessibility to both local and district centre stores (see Table 3.1.1, page 146) and Roath is also located closest to the city centre, which for the purpose of this study, is designated as a district centre

(Figure 3.1.1, page 145). Thus, it is likely that relative to Roath, the other study areas do not have as good accessibility to district centre stores which, consequently may lead to longer durations of local store choice.

The exponential model estimates the covariates corresponding to license ownership (LIC) and the panellists *perceived* shopping frequency of 1 to 2 times a week (FREQ1) as significant but neither of these covariates were estimated as significant influences on local store durations in any of the other models (see Table 4.3.2). These findings may simply indicate 'spurious' heterogeneity which, as discussed previously, may be a result of the constant hazard rate specification of the exponential model. It is also worth mentioning that both marital status (MART) and household size (HSZ) are seen only to significantly decrease local store durations in the exponential, log–normal and log–logistic models. Furthermore, the covariates representing length of residence of 3 to 10 years (LOR1) and the panellist's *perceived* shopping frequency of 3 to 5 times a week (FREQ2) are estimated as significantly decreasing local store durations in only the exponential, Weibull and Gompertz models. This may mean that the influence of marital status (MART) and household size (HSZ) are not adequately represented by the Cox, Weibull and Gompertz models whereas the effect of lengths of residence of 3 to 10 years (LOR1) and the panellist's *perceived* shopping frequency of 3 to 5 times a week may not be adequately represented in the Cox, log–normal and log–logistic models, however, these results also shed doubt on the effect of these particular covariates on local store durations.

The parametric estimates obtained for the case of district store durations are given in Table 4.3.3 (page 221). A Gompertz model with δ=–0.018 and λ=0.019 appears to best describe the district store durations ($\mathscr{L}$=–1906.8). The log–normal and log–logistic models provide similar representations of the district store durations whilst the Weibull and the exponential models give noticeable poorer fits

Table 4.3.3: Model parameter estimates for the district store durations including the influence of exogenous covariates

Regressor Variable	Model Parameter Estimates					
	Cox	Exponential	Weibull	Gompertz	Log-normal	Log-logistic
constant	-	4.238 (0.359)	4.281 (0.528)	3.574 (0.455)	3.571 (0.613)	3.596 (0.564)
DFO	0.403** (0.116)	0.444** (0.094)	0.525** (0.143)	0.395** (0.117)	0.540** (0.158)	0.573** (0.151)
LIC	0.484** (0.133)	0.601** (0.107)	0.668** (0.164)	0.489** (0.139)	0.703** (0.193)	0.682** (0.187)
AGE	0.171* (0.068)	0.213** (0.054)	0.228** (0.082)	0.172** (0.067)	0.122 (0.087)	0.169* (0.083)
MART	0.162 (0.166)	0.327* (0.155)	0.323 (0.229)	0.196 (0.189)	0.267 (0.223)	0.220 (0.235)
YC	0.187 (0.144)	0.163 (0.126)	0.195 (0.190)	0.169 (0.156)	0.252 (0.196)	0.271 (0.199)
OC	0.183 (0.149)	0.169 (0.118)	0.183 (0.176)	0.181 (0.147)	0.244 (0.201)	0.259 (0.198)
HSZ	-0.249** (0.054)	-0.296** (0.047)	-0.331** (0.071)	-0.252** (0.057)	-0.315** (0.075)	-0.329** (0.077)
ADS	1.540** (0.227)	2.063** (0.210)	2.319** (0.321)	1.585** (0.247)	1.934** (0.285)	2.115** (0.298)
LOR1	0.108 (0.170)	0.102 (0.138)	0.162 (0.204)	0.113 (0.167)	0.361 (0.228)	0.344 (0.210)
LOR2	0.118 (0.183)	0.139 (0.152)	0.160 (0.224)	0.109 (0.188)	0.428 (0.253)	0.308 (0.234)
FREQ1	0.422** (0.134)	0.597** (0.107)	0.669** (0.163)	0.450** (0.136)	0.575** (0.182)	0.586** (0.182)
FREQ2	0.366** (0.135)	0.401** (0.116)	0.489** (0.176)	0.363* (0.147)	0.703** (0.189)	0.666** (0.198)
Rhiwbina	-0.705* (0.280)	-0.908** (0.222)	-1.058** (0.321)	-0.711** (0.271)	-1.062** (0.355)	-1.130** (0.314)
Llanederyn	0.754* (0.376)	0.813* (0.339)	1.026* (0.475)	0.760 (0.391)	1.088* (0.449)	1.101** (0.427)
Llanrumney	-0.744 (0.398)	-1.151** (0.350)	-1.216* (0.493)	-0.777 (0.406)	-0.861 (0.479)	-0.934* (0.451)
Rumney	-0.776* (0.309)	-1.083** (0.249)	-1.203** (0.367)	-0.787** (0.308)	-0.914* (0.409)	-1.072** (0.383)
Heath	-0.909** (0.303)	-1.295** (0.246)	-1.404** (0.365)	-0.916** (0.308)	-1.899** (0.410)	-1.256** (0.390)
Whitchurch	-1.028** (0.295)	-1.391** (0.228)	-1.522** (0.342)	-1.027** (0.287)	-1.285** (0.400)	-1.379** (0.378)
Cathays	-0.914** (0.319)	-1.286** (0.270)	-1.432** (0.395)	-0.946** (0.331)	-1.141** (0.422)	-1.285** (0.400)
α/[δ]	-	1.000	0.769	[-0.018]	0.615	1.074
λ/[λ_0]	-	0.009	0.008	[0.019]	0.016	0.016
Log-likelihood	-2170.1†	-1970.0	-1947.0	-1906.8	-1928.1	-1927.7

* significant at the 95% level; ** significant at the 99% level

† based on partial likelihood

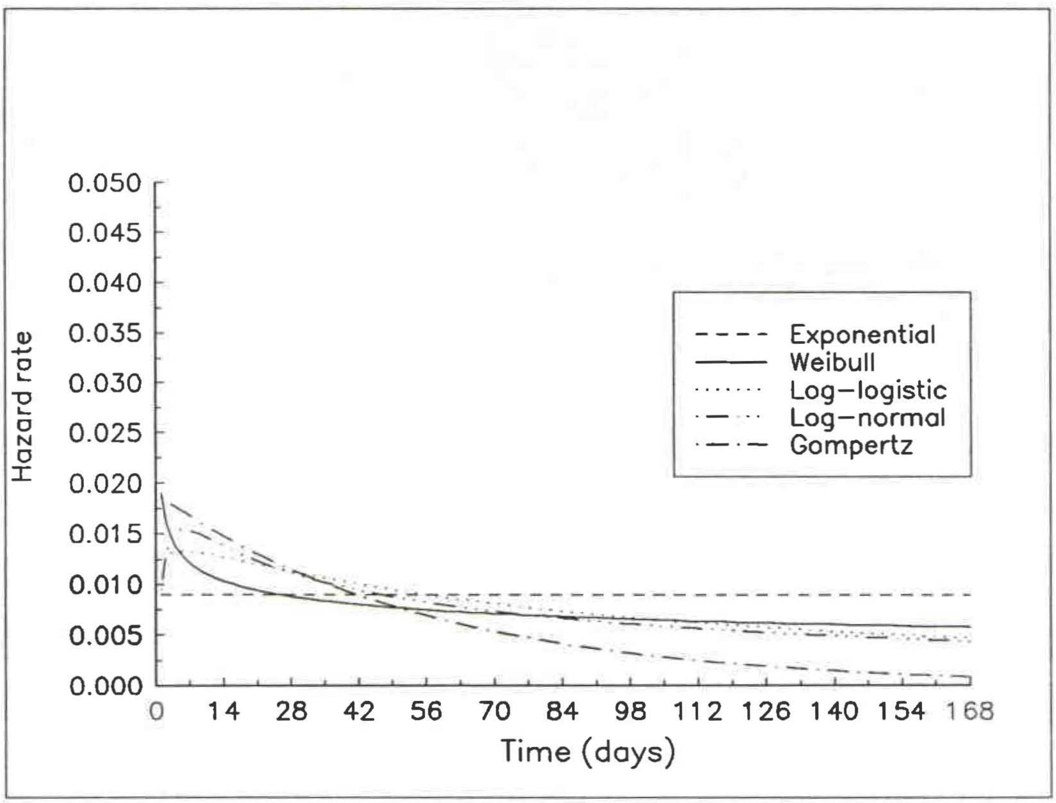


Figure 4.3.3: Hazard rate curves estimated at the mean of the exogenous covariates for the district store durations

to this data. Recall that a Gompertz distribution with $\mathscr{L}$=–2044.9 was also found to best describe the district store durations when covariates were not included in the estimates (Table 4.2.4). A likelihood ratio test of the null hypothesis, $H_0:\beta=0$, for the Gompertzs model results in a χ^2=276.2 with 20 degrees of freedom and therefore, the null hypothesis of no significant influence of covariates on district store durations is rejected at the 99.9% confidence level.

Figure 4.3.3 (page 222) illustrates the estimated hazard rate curves calculated at the mean of the covariates for the district store durations. Both the Gompertz and the Weibull models exhibit monotonically decreasing hazards with increasing duration, ie. negative duration dependence. Both of these models initially possess approximately the same values in the hazard rate but the Gompertz has a much more gradually declining hazard rate in the very short durations (ie. those less than about 4 days), after which time, the Gompertz steadily decreases. On the other hand, the Weibull hazard exhibits a steeper decline over the shorter durations (ie. those less than approximately 7 days) than the Gompertz model, and thereafter the Weibull hazard rate decreases gradually, becoming almost constant after durations of approximately 56 days. The log–normal and the log–logistic models both produce nonmonotonic distributions. The log–logistic exhibits positive duration dependence over the very short durations (ie. those less than about 4 days) whereas the log–normal increases more slowly, exhibiting positive duration dependence for slightly longer durations (ie. those less than 7 days). After reaching their maximum hazard rate values, both the log–logistic and the log–normal models exhibit negative duration dependence and approximate each other for durations of about 35 days onwards.

It is interesting to compare the distributional forms of duration dependence derived for the district store durations with those obtained for the local store durations. Recall that a nonmonotonic distribution estimated by the log–normal model was found to best describe the local store durations (see Figure 4.3.2) whereas a monotonically decreasing Gompertz distribution is found to best represent the district store durations (Figure 4.3.3). These results indicate that different distributional forms of duration dependence may be associated with district store choice as opposed to local store choice when the behavioural variation due to measured sources of population heterogeneity is explicitly controlled. Both positive and negative duration dependence are seen to occur for the local store durations whereas only negative duration dependence is seen for the district store durations.

The coefficient estimates listed in Table 4.3.3 indicate that covariates representing deep freezer ownership (DFO), possession of a driver's license (LIC), the panellist's age (AGE), household size (HSZ), accessibility to district stores (ADS) and the *perceived* frequency of weekly shop visits (FREQ1 and FREQ2), as well as the majority of dummy variables representing the study areas, are all significant influences on the length of district store durations. For reasons stated earlier, it is perhaps not surprising that deep freezer ownership (DFO) positively increases durations of district store choice as district stores are more likely to carry the larger inventory stocks, which have been reasoned to be associated with deep freezer ownership which, in turn, may lead to lower purchasing frequencies and thus longer durations of district store choice. Furthermore, individuals who purchase a deep freezer may do so because they *intend* to purchase at district stores which could result in a predisposition towards district store shopping and hence longer durations of district store choice. License ownership (LIC) is also seen to increase the durations of district store choice, perhaps reflecting the notion that possessing a driver's license may encourage larger volumes of items to be purchased on any one store visit (leading to lower purchasing frequencies) and/or that district store visits may be associated with driver's license possession, as district stores are more likely to provide adequate parking facilities, so that lower store–type switching rates may result in longer durations of district store choice. It is interesting to note that possession of a driver's license (LIC) is seen to significantly influence the district store durations whereas the panellist's *perceived* use of a car for shopping (USEC) and the number of cars owned by the household (NCAR) were not found to be important influences on the duration between store switches (see Figure B.1, Appendix B). It is possible that a panellist's perception of the use of a car for shopping (USEC) may not adequately reflect car usage for shopping and is likely to be, at best, an underestimate of the actual use of a car for shopping trips. Furthermore, the number of cars owned by the household (NCAR) does not necessarily mean that the panellist used a car for shopping purposes. On the other hand, if a panellist possessed a driver's license (LIC) it is more likely that if a car is available it may be used for shopping, which, in turn, could explain why driver's license ownership (LIC) provides a better representation of the influence of car accessibility for this data compared to either of the other two variables.

The panellist's age (AGE) is also seen to positively increase durations of district store choice and was also seen to positively effect durations of local store choice (Table 4.3.2). These findings suggest that lower purchasing rates and/or a tendency towards repeat visits to the same store type, which have been reasoned to occur with increasing age, may increase durations of 'loyalty' to both local and district stores. In other words, a tendency towards habitual store choice behaviour to either local or district stores appears to occur with increasing age. Household size (HSZ) is seen to decrease durations of district store choice and was also seen to have a negative effect on the local store durations (Table 4.3.2). These results provide support for the notion that while larger households may be more likely to shop at district stores, they may also tend to supplement inventory with purchases at local stores. Consequently, larger households may be more likely to switch between store types than smaller households which, in turn, may result in shorter durations of habitual choice towards either store type. The *perceived* rate of weekly shopping is related to longer durations of district store choice. Recall from Section 4.1 that FREQ1 corresponds to shopping rates of 1 to 2 times a week, FREQ2 reflects rates of 3 to 5 times a week and the base category represents 'irregular' shoppers. These results indicate that those panellists who perceive themselves as more regular weekly shoppers are associated with longer durations of district store choice which, in turn, implies that regular purchasing may lead to more habitual choice of district stores compared to 'irregular' purchasing behaviour.

From Table 4.3.3 it appears as though living in all the study areas, with the exception of Llanederyn, increases the hazard rate associated with switching from a district store to a local store relative to the base (category) study area of Roath. Comparing this with the estimates for the local store durations (Table 4.3.2), it is apparent that, with the exception of Llanederyn, living in these same areas appears to increase the durations associated with local store choice. These results may reflect some type of inherent differences in the Rhiwbina, Llanrumney, Rumney, Heath, Whitchurch and Cathays relative to Roath, such as different socio–economic characteristics, which could result in a tendency towards habitual choice of local stores. However, it is perhaps more likely that these results reflect the fact that Roath is located closest to the city centre which, in this study, is classified as a district centre (see Figure 3.1.1, page 145). Thus relative to Roath, the other study areas, with the exception of Llanederyn, may have poorer accessibility to district stores and hence panellists living in these areas may tend to choose local stores more frequently which, in turn, may lead to shorter durations of district store choice. As mentioned previously, Llanederyn is distinguished from the other study areas in having good accessibility to district centre stores and poor accessibility to local centre stores (see Table 3.1.1, page 146). Therefore, panellists living in Llanederyn may be more likely to choose district stores for the majority of their purchases and consequently, this may lead to longer durations of district store choice.

4.3.1 The Influence of Repeat Visits

The findings described in Section 4.3 consider the influence of covariates on duration excluding an explicit measure for the number of interpurchases (NIP). Recall from Section 4.1 that in observational terms, long durations between store type switches can result from repeat visits to the same store type and/or low purchasing frequencies. The number of interpurchases (NIP) serves as a proxy measure for the purchasing frequency which occurs while the same store type is repeatedly visited for successive purchases and thus controls for the 'reinforcement' effect associated with repeat visits to the same store type as well as the purchasing frequency effect occurring in habitual store–type choice. Hence, it is more than likely that the mainly negative duration dependence identified in Section 4.3 reflects the fact that duration increases with increasing numbers of interpurchases (NIP) and hence the hazard rate associated with store–type switching would decrease. Therefore, a covariate representing the number of interpurchases (NIP) was added to the list of covariates examined previously as indicated in the format of equation (4.1.7), and parametric estimates for the Cox, exponential, Weibull, Gompertz, log–normal and log–logistic models were derived for *all* durations and are listed in Table 4.3.4 (page 228). Furthermore, the corresponding hazard rate curves, estimated at the mean value of the covariates, were produced and are illustrated in Figure 4.3.4 (page 229).

From Table 4.3.4 it is apparent that when the number of interpurchases (NIP) covariate is included in the model estimates, a log–logistic model with α=1.668 and λ=0.023 best describes the durations between store switches. Conversely, the exponential model gives the worst fit to these durations and the Weibull and Gompertz models provide only slight improvements over that of the

Table 4.3.4 Model parameter estimates for *all* durations including the influence of the number of interpurchases (NIP) covariate

Regressor Variable	Model Parameter Estimates					
	Cox	Exponential	Weibull	Gompertz	Log-normal	Log-logistic
constant	-	2.750 (0.339)	2.790 (0.296)	2.654 (0.364)	2.155 (0.333)	2.249 (0.302)
NIP	0.332** (0.018)	0.353** (0.010)	0.347** (0.011)	0.331** (0.014)	0.256** (0.010)	0.312** (0.008)
DFO	0.312** (0.835)	0.315** (0.082)	0.311** (0.070)	0.302** (0.086)	0.304** (0.083)	0.306** (0.077)
LIC	0.371** (0.105)	0.367** (0.109)	0.362** (0.094)	0.350** (0.114)	0.357* (0.106)	0.343** (0.102)
AGE	0.148** (0.049)	0.163** (0.044)	0.161** (0.039)	0.150** (0.047)	0.137** (0.047)	0.111** (0.040)
MART	-0.227* (0.115)	-0.195 (0.122)	-0.189 (0.107)	-0.194 (0.128)	-0.203 (0.114)	-0.231 (0.107)
YC	0.031 (0.098)	0.001 (0.099)	0.007 (0.085)	0.004 (0.104)	-0.012 (0.103)	-0.042 (0.098)
OC	-0.222* (0.110)	-0.274* (0.107)	-0.272** (0.093)	-0.241* (0.112)	-0.106 (0.106)	-0.123 (0.099)
HSZ	-0.248** (0.038)	-0.256** (0.040)	-0.254** (0.035)	-0.243** (0.043)	-0.249** (0.039)	-0.238** (0.037)
ADS	0.383* (0.156)	0.483** (0.139)	0.484** (0.120)	0.426** (0.147)	0.224 (0.158)	0.179** (0.132)
LOR1	0.108 (0.120)	0.105 (0.112)	0.891 (0.097)	0.108 (0.119)	0.141 (0.120)	0.215 (0.107)
LOR2	-0.221 (0.137)	0.174 (0.123)	0.166 (0.106)	0.184 (0.130)	0.192 (0.137)	0.301 (0.123)
FREQ1	0.157 (0.092)	0.177 (0.097)	0.168* (0.085)	0.173 (0.102)	0.208* (0.094)	0.212* (0.107)
FREQ2	0.300** (0.097)	0.304** (0.095)	0.293** (0.082)	0.295** (0.101)	0.276** (0.098)	0.320** (0.095)
Rhiwbina	-0.017 (0.191)	-0.063 (0.173)	-0.066 (0.150)	-0.390 (0.185)	0.176 (0.185)	-0.049 (0.157)
Llanederyn	0.445 (0.276)	0.441 (0.258)	0.425 (0.223)	0.438 (0.273)	0.637* (0.263)	0.399 (0.231)
Llanrumney	-0.0712 (0.267)	-0.180 (0.244)	-0.191 (0.211)	-0.132 (0.257)	0.177 (0.261)	-0.012 (0.223)
Rumney	-0.023 (0.214)	-0.941 (0.205)	-0.100 (0.177)	-0.614 (0.218)	0.203 (0.216)	-0.003 (0.188)
Heath	0.256 (0.212)	0.221 (0.194)	0.220 (0.168)	0.225 (0.207)	0.436* (0.214)	0.204 (0.187)
Whitchurch	-0.364 (0.210)	-0.053 (0.198)	-0.059 (0.171)	-0.379 (0.212)	0.233 (0.210)	0.242 (0.190)
Cathays	-0.028 (0.228)	-0.135 (0.218)	-0.138 (0.189)	-0.895 (0.233)	0.144 (0.228)	-0.045 (0.201)
STYP	0.482** (0.074)	0.475** (0.079)	0.455** (0.068)	0.465** (0.083)	0.602** (0.073)	0.583** (0.070)
$\alpha/[\delta]$	-	1.000	1.089	[-0.004]	0.901	1.668
$\lambda/[\lambda_0]$	-	0.013	0.013	[0.015]	0.026	0.023
Log-likelihood	-4545.0†	-3271.3	-3266.5	-3267.3	-3253.3	-3226.6

* significant to the 95% level; ** significant to the 99% level; † based on partial likelihood

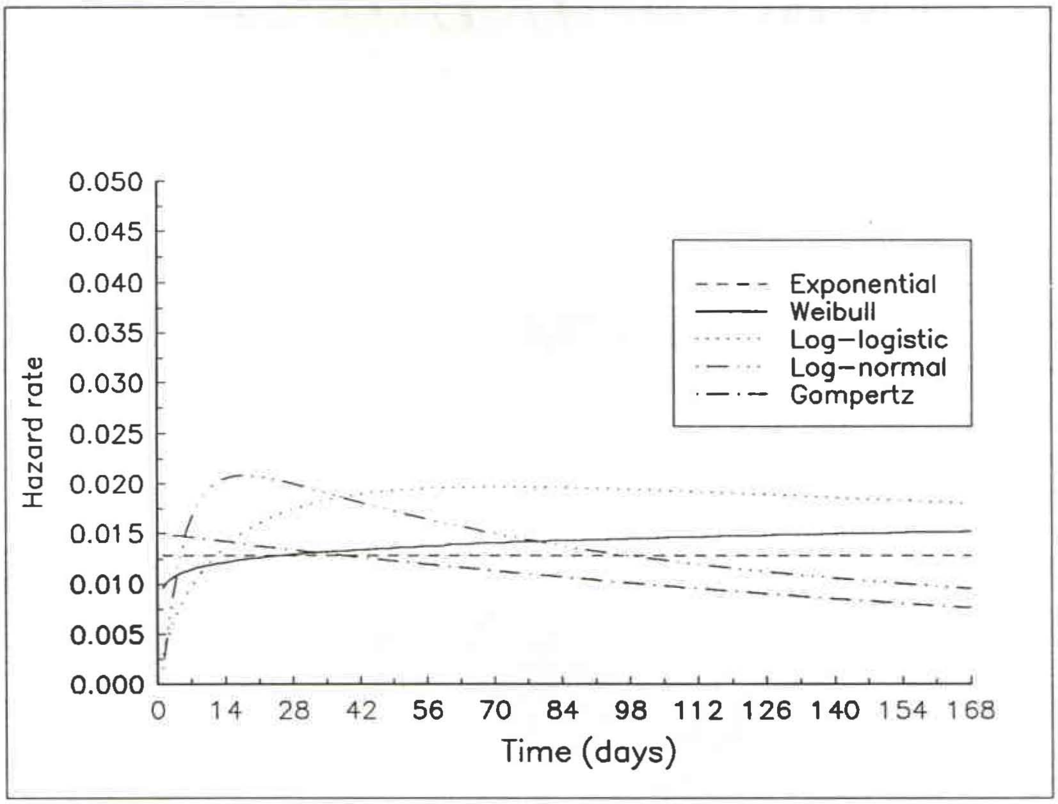


Figure 4.3.4: Hazard rate curves estimated at the mean of the covariates for *all* durations including the number of interpurchases (NIP) covariate

exponential model. Likelihood ratio tests indicate that a significant improvement in fit at the 99.9% confidence level occurs for all of the models when the number of interpurchases (NIP) covariate is included in model estimates. Thus inclusion of the number of interpurchases (NIP) results in a significant improvement in representing the observed durations between store–type switches.

The estimated hazard rate curves shown in Figure 4.3.4 indicate that both the log–normal and log–logistic models estimate nonmonotonic distributions for duration dependence. The log–logistic hazard rate reaches a maximum value at durations of approximately 56 days after which time, the log–logistic decreases very gradually. The log–normal, on the other hand, possesses a larger rate of change in the hazard rate than the log–logistic, reaching a maximum hazard value in earlier durations, ie. those of about 14 days, and decreasing thereafter. The Gompertz hazard rate monotonically decreases from λ_0=0.015 whereas the Weibull hazard monotonically increases from λ=0.013 and, by durations of approximately 30 days, these two distributions intersect. The better fit of the log–logistic relative to that of the log–normal model may be because the log–normal estimates a higher rate of change in the hazard in the shorter durations which may be a reflection of the tendency of the log–normal to approach zero as duration (ie. *t*) increases. Therefore it appears as though controlling for the number of interpurchases (NIP) has the effect of changing the distributional form of duration dependence from monotonically decreasing over all durations to a nonmonotonic distribution, exhibiting positive duration dependence over durations of about 56 days and negative duration dependence thereafter.

Referring to Table 4.3.4, and for reasons stated previously, it is perhaps not surprising that the covariates representing deep freezer ownership (DFO), possession of a driver's license (LIC), the panellist's age (AGE) and the accessibility to district stores (ADS) are estimated as significantly increasing the durations between store switches. Each of these covariates have been reasoned to decrease the switching rate between store types and thus inclusion of a measure of the frequency of purchasing associated with a particular store type (as measured by the number of interpurchases (NIP)) would not likely alter the influence of these covariates on duration. Also, household size (HSZ) is still seen to significantly decrease the durations when the number of interpurchases (NIP) is included in model estimates which provides support for the previously stated notion that larger households may tend to frequently 'top up' inventory stocks with trips to local stores in order to maintain adequate inventory to meet the higher consumption levels which may be associated with larger households.

It is interesting to note that across all of the models of Table 4.3.4, the covariate representing the panellist's *perceived* frequency of purchasing 3 to 5 times a week (ie. FREQ2) is estimated as significantly increasing the durations between store switches whilst purchasing 1 to 2 times a week (FREQ1) is estimated as significant in only the Weibull, log–normal and log–logistic models. Recall that when the number of interpurchases (NIP) was not specified FREQ2 was estimated as significant in only the log–normal and log–logistic models (see Table 4.3.1). Therefore, it appears as though when the number of interpurchases (NIP) is measured, panellist's who perceive themselves as more regular weekly shoppers tend to have longer durations between store–type switches than do panellist's who see themselves as 'irregular' weekly shoppers. It is possible that panellist's who perceive themselves as regular purchasers may make fewer 'topping up' trips (to local stores) compared to those panellist's who tend to purchase 'irregularly', so that longer durations between store switches may occur with more regular shopping behaviour.

With the exceptions of the log–normal and log–logistic models, the covariate reflecting the presence of older children (OC) is estimated to significantly decrease the durations between store–type switches (see Table 4.3.4). The presence of older children is obviously related to household size and it is possible that households with an older child purchase more often at all store types, which may result from higher consumption rates and/or higher store switching rates, so that shorter durations between store–type switches may occur compared to households without older children. This reasoning may also explain why the older children (OC) covariate is not estimated as significant in the log–normal or log–logistic models as these models estimate higher rates of change in the hazard in the shorter duration lengths than the other models (see Figure 4.3.4). In other words, most of the behavioural variation associated with the presence of older children (OC) may be being captured by the distributional form of the hazard resulting from a log–normal or log–logistic specification. However, considering that the log–logistic model best fit these durations also sheds doubt on the effect of older children on the durations between store–type switches. Store type (STYP) also appears to significantly effect the durations between store switches. This provides further support for the notion that the tendency towards habitual store choice behaviour may be different for the district store durations than the local store durations and this was further investigated by separate analysis of local store durations and district store durations.

In terms of local store durations, Table 4.3.5 (page 233) shows that a log–logistic model ($\mathscr{L}$=–1492.3) with parameters α=1.749 and λ=0.058 provides a slightly better fit than a log–normal distribution ($\mathscr{L}$=–1494.4). The Gompertz, Weibull and exponential models estimate similar log–likelihood values and appear not to fit the data as well as the nonmonotonic distributions. These findings indicate that the two parameter Gompertz and Weibull models provide little improvement in representing the local store durations compared to the (one–parameter) exponential model. Recall from Table 4.3.2 that a log–normal

Table 4.3.5: Model parameter estimates for the local store durations including the influence of the number of interpurchases(NIP) covariate

Regressor Variable	Model Parameter Estimates					
	Cox	**Exponential**	**Weibull**	**Gompertz**	**Log-normal**	**Log-logistic**
constant	-	2.018	2.025	1.999	1.898	2.010
		(0.530)	(0.474)	(0.563)	(0.467)	(0.459)
NIP	0.289**	0.326**	0.324**	0.300**	0.279**	0.293**
	(0.028)	(0.019)	(0.018)	(0.044)	(0.016)	(0.013)
DFO	0.165	0.189	0.188	0.173	0.199	0.216*
	(0.117)	(0.113)	(0.101)	(0.121)	(0.110)	(0.106)
LIC	0.410**	0.452**	0.462**	0.408*	0.274	0.256
	(0.156)	(0.160)	(0.144)	(0.172)	(0.147)	(0.143)
AGE	0.181**	0.212**	0.210**	0.188**	0.157*	0.130*
	(0.070)	(0.063)	(0.057)	(0.070)	(0.065)	(0.061)
MART	-0.158	-0.130	-0.127	-0.132	-0.158	-0.227
	(0.162)	(0.167)	(0.150)	(0.177)	(0.153)	(0.149)
YC	0.095	0.100	0.114	0.086	0.000	0.009
	(0.138)	(0.146)	(0.130)	(0.152)	(0.138)	(0.137)
OC	-0.343*	-0.422**	-0.423**	-0.368*	-0.346*	-0.297*
	(0.159)	(0.153)	(0.138)	(0.165)	(0.140)	(0.136)
HSZ	-0.163**	-0.182**	-0.182**	-0.169**	-0.155**	-0.160**
	(0.053)	(0.057)	(0.051)	(0.062)	(0.052)	(0.053)
ADS	-0.254	-0.134	-0.120	-0.174	-0.369	-0.510*
	(0.288)	(0.303)	(0.275)	(0.321)	(0.242)	(0.248)
LOR1	0.032	0.027	0.032	0.028	0.203	0.048
	(0.172)	(0.173)	(0.155)	(0.183)	(0.163)	(0.161)
LOR2	0.359	0.355	0.363*	0.349	0.271	0.337
	(0.195)	(0.193)	(0.173)	(0.204)	(0.186)	(0.179)
FREQ1	-0.008	0.002	0.006	0.008	0.004	0.039
	(0.134)	(0.148)	(0.134)	(0.157)	(0.124)	(0.126)
FREQ2	0.134	0.158	0.164	0.144	0.044	0.033
	(0.145)	(0.143)	(0.129)	(0.153)	(0.131)	(0.132)
Rhiwbina	0.299	0.296	0.284	0.283	0.319	0.247
	(0.267)	(0.263)	(0.235)	(0.282)	(0.256)	(0.230)
Llanederyn	0.551	0.582	0.564	0.564	0.558	0.554
	(0.409)	(0.480)	(0.433)	(0.495)	(0.392)	(0.358)
Llanrumney	0.725	0.685	0.684	0.660	0.559	0.524
	(0.408)	(0.395)	(0.354)	(0.414)	(0.373)	(0.348)
Rumney	0.292	0.294	0.299	0.278	0.268	0.247
	(0.315)	(0.316)	(0.283)	(0.336)	(0.305)	(0.277)
Heath	0.677*	0.737*	0.740**	0.668*	0.630*	0.529
	(0.309)	(0.298)	(0.269)	(0.327)	(0.298)	(0.271)
Whitchurch	0.490	0.570	0.570*	0.504	0.479	0.380
	(0.304)	(0.299)	(0.270)	(0.327)	(0.291)	(0.270)
Cathays	0.602	0.558	0.555	0.541	0.519	0.542
	(0.352)	(0.369)	(0.332)	(0.389)	(0.318)	(0.304)
α/[δ]	-	1.000	1.068	[-0.005]	0.991	1.749
λ/[λ_0]	-	0.034	0.033	[0.039]	0.057	0.058
Log-likelihood	-2021.3†	-1529.8	-1528.3	-1526.8	-1494.4	-1492.3

* significant at the 95% level; ** significant at the 99% level; † based on partial likelihood

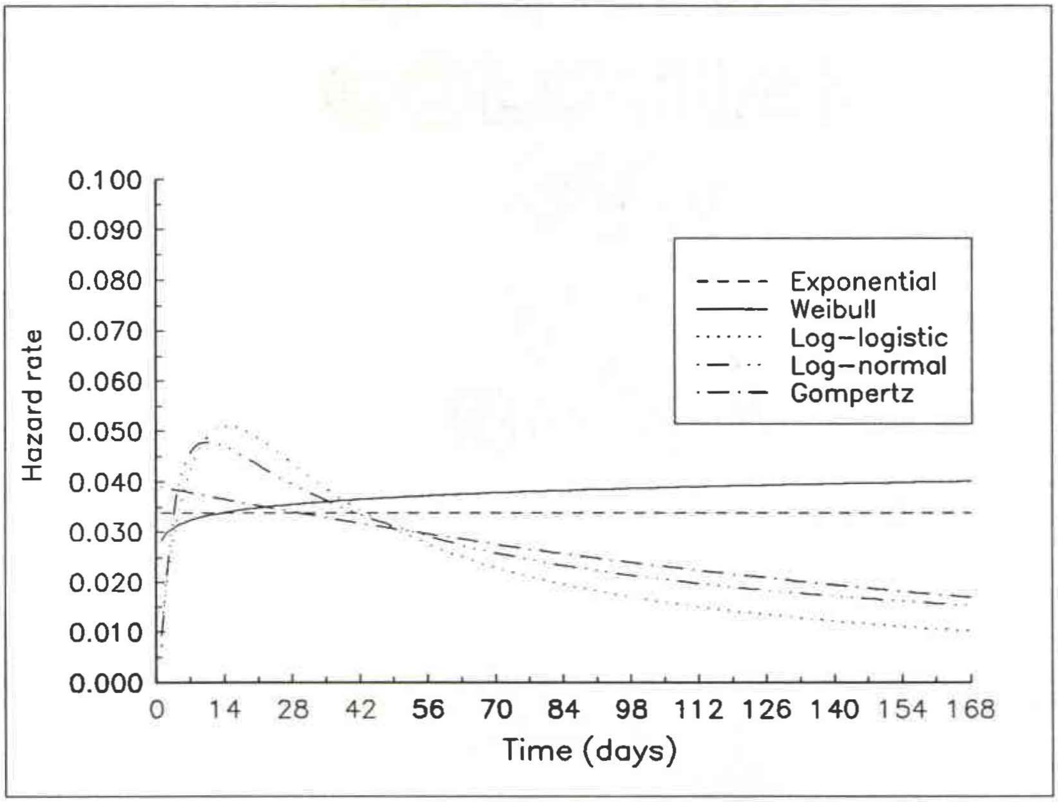


Figure 4.3.5: Hazard rate curves estimated at the mean value of the covariates for the local store durations including the influence of the number of interpurchases (NIP) covariate

model (with $\mathscr{L}$=–1654.6) provided a slightly better representation of the local store durations than a log–logistic model when the number of interpurchases (NIP) covariate was not included in the list of regressor variables. Comparing this with the log–likelihood estimate for the log–normal model in Table 4.3.5 results in a χ^2=320.4 with 1 degree of freedom which is significant at the 99.9% level. Therefore, the inclusion of the number of interpurchases (NIP) covariate is seen to result in a significant improvement in fit to the local store durations.

Figure 4.3.5 (page 234) illustrates the estimated hazard rate curves for the local store durations calculated at the mean of the covariates. The Weibull model exhibits a monotonically increasing hazard rate whilst the Gompertz model is seen to estimate a monotonically decreasing hazard rate. It is likely that the negative duration dependence associated with the Gompertz model reflects the restriction of the Gompertz distribution to approach zero at longer durations. Alternatively, both the log–logistic and the log–normal distributions possess nonmonotonic hazard rates. Compared to the log–logistic distribution, the log–normal is seen to estimate slightly larger rates of change in the hazard rate until durations of approximately 7 days, reaching a maximum value by durations of about 10 days and then slowly declining for the remaining durations. The log–logistic distribution, on the other hand, reaches a maximum at slightly longer durations (ie. those of approximately 14 days), after which time the log–logistic distribution exhibits a larger rate of decline in the hazard rate than the log–normal. These results indicate that a monotonic distributional form does not appear to adequately represent the local store durations which implies that the 'true' hazard rate for the local store durations possesses a nonmonotonic distributional form.

From Table 4.3.5, it is apparent that increasing numbers of interpurchases (NIP) at local stores significantly decreases the hazard rate associated with switching from a local store to a district store. It is interesting to compare the estimates of Table 4.3.5 with those derived when the number of interpurchases (NIP) covariate was not included in parameter estimates (Table 4.3.2). For the local store durations, controlling for the number of interpurchases (NIP) essentially measures the purchasing frequency associated with repeat visits to local stores. The panellist's age (AGE) is the only covariate which is estimated as significantly influencing the local store durations in both Tables 4.3.5 and 4.3.2. This implies that older panellists appear to exhibit a tendency towards habitual choice of local stores which may lead to longer durations of local store choice and that this effect may outweigh that associated with the influence of lower purchasing frequencies, which has also been reasoned to occur with increasing age.

Accessibility to district stores (ADS) was estimated as significantly decreasing local store durations in all of the models when the number of interpurchases (NIP) was not included in parameter estimates, but is seen to significantly decrease local store durations in only the log–logistic model when the the number of interpurchases (NIP) covariate is included (see Table 4.3.5). Thus by controlling for the number of interpurchases (NIP) there appears to be no appreciable difference in local store durations between households which have or do not have good accessibility to district stores. However, given that accessibility to district stores is estimated a significantly decreasing local store durations in the best fitting model (ie. the log–logistic model), it is possible that panellists with good accessibility to district stores may tend to switch to stores more frequently compared to panellists who do not have good accessibility, which, in turn, may lead to shorter durations of local store choice. Similarly, the 'regional effect' seen to influence the local store durations in Table 4.3.2 is generally not apparent when the number of interpurchases (NIP) covariate is included in the models. It is possible that the geography of the study areas affects the behaviour associated with repeat visits to local stores so that by controlling for repeat visits (ie. by explicitly measuring the number of interpurchases (NIP)), the 'regional effect' is largely accounted for and hence the influence of the study areas is no longer estimated as being significant.

Alternatively, when the number of interpurchases (NIP) is controlled for in model estimates, the log–logistic model estimates deep freezer ownership (DFO) as significantly increasing durations of local store choice (Table 4.2.5) whereas deep freezer ownership (DFO) was not found to be significant in any of the models when the number of interpurchases (NIP) covariate was not included (Table 4.3.2). Longer durations between repeat visits to local stores may be promoted by deep freezer ownership (DFO), which may result from larger inventory purchases on any one store visit by panellists who own a deep freezer, compared to those who do not own a deep freezer. It should also be noted that license ownership (LIC) is seen to significantly increase the local store durations in all but the log–normal (t–ratio=1.87) and log–logistic (t–ratio=1.70) models, when the number of interpurchases is controlled for (Table 4.3.5), but was not estimated as significant to local store durations in Table 4.3.2. This implies that longer durations of local store choice are further promoted by license ownership. In other words, panellists who tend to habitually choose local stores may be more likely to purchase larger volumes of items if they own a drivers license compared to those who do not possess a license which, in turn, may lead to longer durations of local store choice. Furthermore, both the covariates representing the presence of older children (OC) and household size (HSZ) are seen to significantly decrease local store durations in Table 4.3.5, but older children (OC) was not estimated as significant in any of the models and household size (HSZ) was significant in the exponential, log–normal and log–logistic models when the number of interpurchases (NIP) covariate was not included (see Table 4.3.2). These results imply that households with older children and larger households are more likely to switch from local stores to district stores and this may be a result of the higher consumption rates believed to be associated with these households. Households with older children (OC) as well as larger households have both been reasoned to exhibit higher store switching rates than household without older children and smaller households because of a possible tendency for supplementing district store purchases with frequent 'topping up' trips at local stores that may be due to higher consumption levels. Therefore, it appears as though the influence of this higher store switching rate becomes significant to decreasing the longer durations which occur with increasing numbers of interpurchases.

In terms of district store durations, Table 4.3.6 (page 239) indicates that when the number of interpurchases (NIP) is controlled for a Weibull model with parameters α=1.208 and λ=0.007 gives a slightly better fit to the district store durations than a log–logistic model (with α=1.690 and λ=0.012). Both the exponential and Gompertz models are seen to give the same poor fit to the district store durations. Likelihood ratio tests indicate that when the number of interpurchases (NIP) covariate is included in model estimates a significant improvement in fit to the district store durations at the 99.9% confidence level is obtained for <u>all</u> of the models. These results indicate that controlling for the endogenous influence of the number of interpurchases (NIP) results in a substantially improved representation of the district store durations.

The hazard rate curves for district store durations are estimated at the mean of the covariates and are illustrated in Figure 4.3.6 (page 240). The mean number of interpurchases at district stores is approximately twice that of local stores (5.58 against 2.60). On average, therefore, almost twice the number of repeat visits to district stores occurs before switching to local stores as compared to switches from local to district stores. As shown in Figure 4.3.6 the Gompertz distribution is seen to be very similar to the exponential distribution, having an approximately constant

Table 4.3.6: Model parameter estimates for the district store durations including the influence of the number of interpurchases (NIP) covariate

Regressor Variable	Model Parameter Estimates					
	Cox	**Exponential**	**Weibull**	**Gompertz**	**Log-normal**	**Log-logistic**
constant	-	4.022 (0.469)	4.097 (0.354)	4.010 (0.498)	3.076 (0.441)	3.181 (0.395)
NIP	0.333** (0.026)	0.325** (0.014)	0.309** (0.014)	0.324** (0.018)	0.217** (0.012)	0.281** (0.011)
DFO	0.429** (0.121)	0.382** (0.133)	0.352** (0.099)	0.381** (0.133)	0.393** (0.115)	0.383** (0.110)
LIC	0.327* (0.148)	0.302 (0.186)	0.265 (0.140)	0.302 (0.187)	0.423** (0.143)	0.372** (0.146)
AGE	0.077 (0.072)	0.075 (0.070)	0.067 (0.054)	0.074 (0.071)	0.085 (0.064)	0.078 (0.054)
MART	-0.273 (0.167)	-0.220 (0.202)	-0.210 (0.153)	-0.220 (0.203)	-0.158 (0.160)	-0.224 (0.159)
YC	-0.078 (0.146)	-0.112 (0.162)	-0.125 (0.120)	-0.111 (0.163)	0.034 (0.143)	-0.069 (0.136)
OC	-0.070 (0.160)	-0.116 (0.180)	-0.123 (0.136)	-0.114 (0.181)	0.138 (0.147)	0.525 (0.140)
HSZ	-0.355** (0.058)	-0.333** (0.066)	-0.320** (0.050)	-0.332** (0.069)	-0.322** (0.054)	-0.302** (0.054)
ADS	0.778** (0.208)	0.786** (0.192)	0.755** (0.142)	0.782** (0.194)	0.704** (0.207)	0.651** (0.173)
LOR1	0.271 (0.175)	0.293 (0.174)	0.248 (0.129)	0.292 (0.174)	0.287 (0.166)	0.365* (0.144)
LOR2	0.188 (0.201)	0.152 (0.195)	0.128 (0.146)	0.152 (0.196)	0.205 (0.189)	0.309 (0.165)
FREQ1	0.302* (0.134)	0.329* (0.148)	0.288** (0.111)	0.323* (0.149)	0.422** (0.131)	0.370** (0.129)
FREQ2	0.463** (0.137)	0.443** (0.160)	0.402** (0.121)	0.442** (0.161)	0.515** (0.137)	0.542** (0.134)
Rhiwbina	-0.372 (0.284)	-0.413 (0.264)	-0.380 (0.198)	-0.410 (0.265)	-0.122 (0.254)	-0.350 (0.215)
Llanederyn	0.202 (0.386)	0.189 (0.374)	0.137 (0.284)	0.191 (0.374)	0.585 (0.337)	0.246 (0.302)
Llanrumney	-0.593 (0.394)	-0.612 (0.373)	-0.629* (0.282)	-0.607 (0.375)	-0.145 (0.350)	-0.429 (0.304)
Rumney	-0.519 (0.317)	-0.530 (0.320)	-0.544* (0.239)	-0.525 (0.321)	-0.086 (0.294)	-0.338 (0.260)
Heath	-0.349 (0.315)	-0.374 (0.325)	-0.393 (0.243)	-0.370 (0.329)	-0.057 (0.296)	-0.199 (0.261)
Whitchurch	-0.755* (0.312)	-0.715* (0.332)	-0.743** (0.246)	-0.710* (0.337)	-0.247 (0.289)	-0.423 (0.268)
Cathays	-0.577 (0.322)	-0.634* (0.317)	-0.614** (0.336)	-0.629 (0.322)	-0.278 (0.307)	-0.553* (0.275)
$\alpha/[\delta]$	-	1.000	1.208	[0.000]	0.889	1.690
$\lambda/[\lambda_0]$	-	0.007	0.007	[0.007]	0.015	0.012
Log-likelihood	-1981.8†	-1717.4	-1707.4	-1717.4	-1735.3	-1708.1

* significant at the 95% level; ** significant at the 99% level; † based on partial likelihood

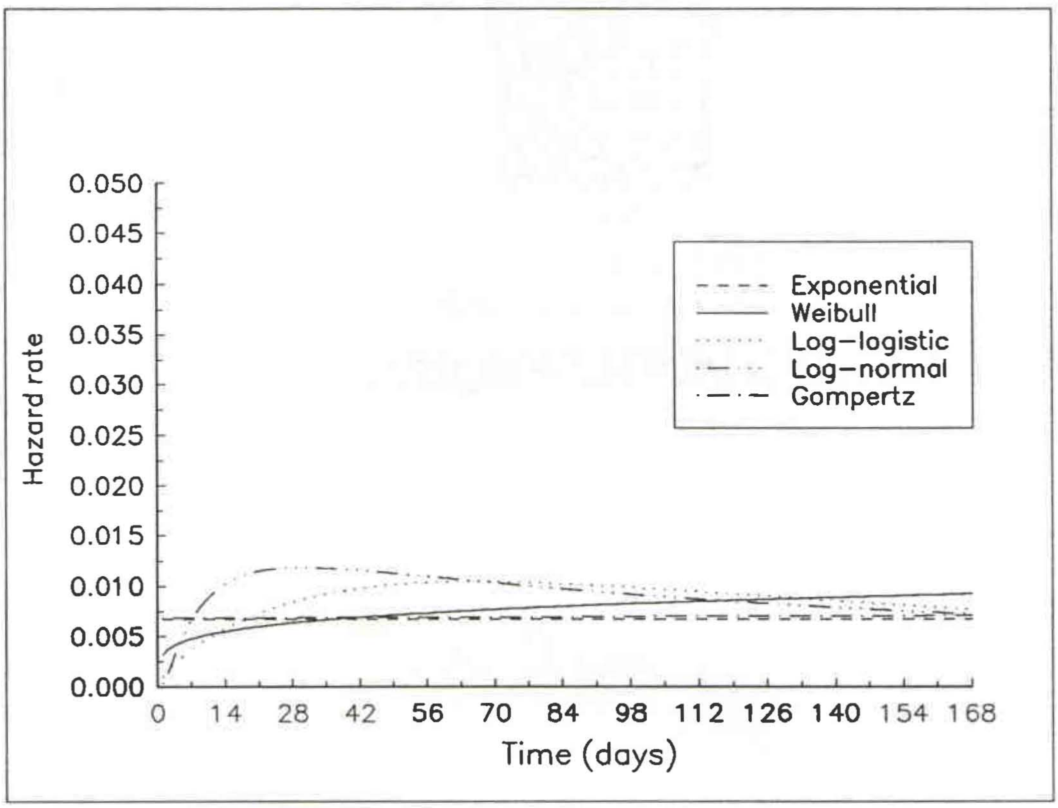


Figure 4.3.6: **Hazard rate curves estimated at the mean of the covariates for the district store durations including the influence of the number of interpurchases (NIP) covariate.**

hazard rate at about λ_0=0.007. The log–normal distribution exhibits the largest increase in the rate of change in the hazard over short durations, reaching a maximum value at durations of approximately 21 days, and then decreases, approximating the same rate of decline in the hazard as the log–logistic for durations of about 91 days, onwards. The log–logistic distribution possesses a larger rate of change in the hazard than either the log–normal or the Weibull distributions in the shorter durations, increasing to a maximum value at durations of about 56 days and then gradually decreasing thereafter. Alternatively, the Weibull initially maintains a higher absolute value of the hazard in the shorter durations (ie. those less than approximately 14 days) than either the log–logistic or the log–normal models, after which time the Weibull continues to gradually decrease over the remaining durations.

Recall that when the number of interpurchases (NIP) covariate was not included in the models, a monotonically decreasing Gompertz hazard provided the best fit to the district store durations (see Figure 4.3.3). However, when the number of interpurchases (NIP) covariate is included in the models, a monotonically increasing Weibull hazard is seen to best describe the district store durations. In other words, by controlling for the number of interpurchases (NIP) the probability of switching from a district store to a local store increases with increasing durations (see Figure 4.3.6). Thus whereas negative duration dependence occurs over all district store durations when the number of interpurchases (NIP) is *not* explicitly considered, positive durations dependence apparently occurs over all district store durations when the number of interpurchases (NIP) is controlled for. It should be noted that the Weibull model gives a small improvement in fit to the district store durations relative to that of the log–logistic model (see Table 4.3.6) and, after durations of approximately 56 days, the log–logistic distribution exhibits negative duration dependence (Figure 4.3.6). Considering that the majority of the durations are observed for duration lengths of 56 days or less (see Figure B.2, Appendix B), it is likely that the 'true' form of the district store hazard rate is increasing over the durations.

Comparing the duration dependence observed for district store choice (Figure 4.3.6) with that found for local store choice (Figure 4.3.5), it seems as though, for the same duration lengths, the absolute values of the hazard rate is roughly four times as large for the local store durations. This, in turn, implies that there is consistently a greater probability of switching from local stores to district stores compared to the probability of switching from a district store to a local store. Moreover, whilst short durations of local store choice (ie. those less than about 14 days) are associated with an increasing hazard rate whereas over these same durations district store choice is associated with a decreasing hazard rate, the absolute values of the district store hazard rate is consistently smaller than that estimated for local stores.

From Table 4.3.6 it is apparent that increasing numbers of interpurchases at district stores significantly decreases the hazard rate, ie. the probability of switching from a district store to a local store. It is interesting to compare Table 4.3.6 with the results obtained when the number of interpurchases (NIP) covariate was not included in the models (Table 4.3.3). For reasons stated earlier, it is perhaps not surprising that deep freezer ownership (DFO), accessibility to district stores (ADS) and the panellist's *perceived* frequency of weekly shopping (FREQ1 and FREQ2) are estimated as significantly increasing durations of district store choice. Each of these covariates has been reasoned to effect the rate of switching between district and local stores and thus controlling for the frequency of district store purchasing (ie. by including the number of interpurchases (NIP) covariate) would not likely alter the influence of these covariates on district store choice behaviour. Furthermore, in both Table 4.3.6 and Table 4.3.3 household size (HSZ) is estimated as significantly decreasing durations of district store choice. This provides further support for the notion that larger households may have a greater tendency to switch between district and local stores simply because of a need to maintain adequate inventory levels to meet the higher household consumption rates.

Alternatively, possession of a driver's license (LIC) is seen to significantly increase the district store durations in only the Cox, log–normal and log–logistic models when the number of interpurchases (NIP) is included in the estimates. Furthermore, the panellist's age (AGE) is not estimated as significant to district store durations when the number of interpurchases (NIP) is controlled for (Table 4.3.6), but was seen to significantly increase the district store durations in all of the models when the number of interpurchases (NIP) was not explicitly considered (see Table 4.3.3). For the district store durations, the number of interpurchases (NIP) covariate essentially measures the frequency of purchasing at district stores and thus it is likely that these covariates may be strongly related to purchasing frequency so that they are no longer estimated as significant when the number of interpurchases (NIP) is measured. Therefore, it is possible that the effect of license ownership (LIC) is to reduce the overall number of trips to stores by encouraging larger inventory purchasing which, in turn, may result in longer durations of district store choice. However, it is also possible that those panellists who tend to habitually choose district stores may do so regardless of whether or not they possess a license. Similarly, the results for the age (AGE) covariate may indicate that panellists who tend to visit district stores may do so irrespective of their age which implies that the influence of age structure on district store choice may be more related to the frequency of purchasing at district stores rather than a preference towards district stores.

It should also be noted that the 'regional effect' which occurred when the number of interpurchases (NIP) covariate was not included in the models is largely not apparent in Table 4.3.6. Therefore, it is possible that the geography of the study areas influences the number of repeat visits to district stores and thus by controlling for the effect of repeat visits (by controlling for the number of interpurchases (NIP)) the influence of the study areas on durations of district store choice is explicitly measured so that the study area variables are generally not estimated as significant.

4.3.2 The Influence of Income

The effect of income status (INC) on duration was not examined in Section 4.3 because income status was not known for 367 of the 1,182 observations in the data set. This translates to income status not being reported by 130 of the 424 panellists who purchased the product category baked beans at least once in the study period. Hence it was thought necessary to try to establish if any inherent differences existed between the durations associated with panellists who *did* report income as opposed to the durations associated with panellists who *did not* report income. The first step in this investigation considered using a dummy covariate representing whether or not a panellist reported income (IREP). This income reporting variable (IREP) was added to the list of the covariates examined previously, but without controlling for the number of interpurchases (NIP) and a Gompertz model was estimated for *all* durations. The influence of income status reporting (IREP) variable was also investigated using a log–logistic model for *all* durations with the number of interpurchases (NIP) controlled for.

The resultant parameter estimates given in Table 4.3.7 (page 245) indicate that the income reporting (IREP) covariate does not significantly influence the length of durations in either of these two cases. The coefficient estimates derived for the Gompertz model are very similar to those obtained when income reporting (IREP) was not included (see Table 4.3.7), although a slight decrease in the location

Table 4.3.7: Model parameter estimates for *all* durations including the influence of the income status reporting (IREP) covariate

Regressor Variable	Model Parameter Estimates			
	Gompertz	Gompertz	Log-logistic	Log-logistic
constant	2.505 (0.333)	2.485 (0.335)	2.249 (0.302)	2.321 (0.302)
IREP	-	0.412 (0.078)	-	-0.127 (0.077)
NIP	-	-	0.312** (0.008)	0.312** (0.008)
DFO	0.264** (0.077)	0.266** (0.078)	0.306** (0.077)	0.296** (0.077)
LIC	0.296** (0.108)	0.296** (0.109)	0.343** (0.102)	0.349** (0.101)
AGE	0.246** (0.047)	0.247** (0.047)	0.111** (0.040)	0.105** (0.040)
MART	-0.044 (0.119)	-0.051 (0.120)	-0.231 (0.107)	-0.206 (0.107)
YC	0.123 (0.095)	0.127 (0.095)	-0.042 (0.098)	-0.052 (0.098)
OC	0.022 (0.105)	0.027 (0.105)	-0.123 (0.099)	-0.143 (0.099)
HSZ	-0.151** (0.037)	-0.152** (0.037)	-0.238** (0.037)	-0.242** (0.037)
ADS	0.679** (0.155)	0.686** (0.155)	0.179** (0.132)	0.163 (0.133)
LOR1	-0.148 (0.101)	-0.146 (0.101)	0.215 (0.107)	0.203 (0.107)
LOR2	0.008 (0.125)	0.004 (0.125)	0.301 (0.123)	0.318** (0.123)
FREQ1	0.046 (0.091)	0.050 (0.091)	0.212* (0.107)	0.205* (0.091)
FREQ2	0.071 (0.089)	0.737 (0.089)	0.320** (0.095)	0.316** (0.095)
Rhiwbina	-0.130 (0.180)	-0.133 (0.180)	-0.049 (0.157)	-0.039 (0.158)
Llanederyn	0.901** (0.279)	0.901** (0.280)	0.399 (0.231)	0.395 (0.232)
Llanrumney	-0.422 (0.266)	-0.463 (0.266)	-0.012 (0.223)	-0.010 (0.224)
Rumney	-0.068 (0.212)	-0.068 (0.212)	-0.003 (0.188)	-0.003 (0.188)
Heath	0.164 (0.204)	0.171 (0.205)	0.204 (0.187)	0.187 (0.188)
Whitchurch	-0.094 (0.198)	-0.854 (0.201)	0.242 (0.190)	0.013 (0.190)
Cathays	-0.189 (0.216)	-0.184 (0.218)	-0.045 (0.201)	-0.062 (0.202)
STYP	0.621** (0.076)	0.622** (0.076)	0.583** (0.070)	0.583** (0.070)
$\alpha/[\delta]$	[-0.024]	[-0.024]	1.668	1.671
$\lambda/[\lambda_0]$	[0.034]	[0.030]	0.023	0.023
Log-likelihood	-3675.6	-3675.4	-3226.6	-3225.2

* significant at the 95% level; ** significant at the 99% level

parameter, λ_0, is noted. A likelihood ratio test comparing the improvement of the Gompertz model including the effect of income reporting (IREP) ($\mathscr{L}$=–3675.4) with that which did not include the income reporting (IREP) covariate ($\mathscr{L}$=–3675.6) gives a χ^2=0.4 with 1 degree of freedom indicating that no significant difference exists between the two models. Comparing the two log–logistic specifications, however, indicates that accessibility to district stores (ADS) is no longer estimated as significant, whilst the covariate representing lengths of residence of 10 or more years (LOR2) becomes significant when income reporting is considered (see Table 4.3.7). The corresponding likelihood ratio test gives a χ^2=2.8 with 1 degree of freedom indicating that a log–logistic model including the effect of income reporting (IREP) results in a better fit to these durations at a significance level of 90%. Therefore, it is possible that a difference exits between the durations observed for the income reporters as opposed to the durations for those panellists who did not report income when the influence of the number of interpurchases (NIP) is explicitly measured.

The effect of the income reporting (IREP) covariate on the durations disaggregated by store type was also investigated and the estimates derived for the local store durations are listed in Table 4.3.8 (page 247) and those corresponding to district store durations are given in Table 4.3.9 (page 248). The resultant estimates for both the local and district store durations which do not control for the number of interpurchases (NIP) are similar to the findings obtained when the covariate representing income reporting (IREP) was not included in the parameter estimates. However, when the number of interpurchases (NIP) covariate is included, differences in the coefficients occur for the local store durations compared to those which were derived when income reporting (IREP) was not considered (Table 4.3.8). In particular, deep freezer ownership (DFO) is no longer estimated as significantly increasing local store durations when income reporting (IREP) is

Table 4.3.8: Model parameter estimates including IREP for the local store durations

Regressor Variable	Model Parameter Estimates			
	Log-normal	Log-normal	Log-logistic	Log-logistic
constant	1.960 (0.658)	1.944 (0.663)	2.010 (0.459)	2.087 (0.460)
IREP	-	0.030 (0.155)	-	-0.126 (0.122)
NIP	-	-	0.293** (0.013)	0.293** (0.013)
DFO	0.090 (0.154)	0.091 (0.154)	0.216* (0.106)	0.205 (0.107)
LIC	0.248 (0.208)	0.247 (0.208)	0.256 (0.143)	0.261 (0.142)
AGE	0.335** (0.092)	0.337** (0.092)	0.130* (0.061)	0.124* (0.061)
MART	-0.461* (0.212)	-0.467* (0.214)	-0.227 (0.149)	-0.203 (0.151)
YC	0.070 (0.193)	0.073 (0.194)	0.009 (0.137)	0.001 (0.138)
OC	-0.151 (0.196)	-0.145 (0.197)	-0.297* (0.136)	-0.321* (0.137)
HSZ	-0.157* (0.073)	-0.157* (0.073)	-0.160** (0.053)	-0.164** (0.053)
ADS	-0.814* (0.337)	-0.812* (0.337)	-0.510* (0.248)	-0.515* (0.246)
LOR1	-0.387 (0.227)	-0.385 (0.227)	0.048 (0.161)	0.040 (0.163)
LOR2	0.177 (0.261)	0.174 (0.262)	0.337 (0.179)	0.356* (0.180)
FREQ1	-0.197 (0.172)	-0.196 (0.172)	0.039 (0.126)	0.032 (0.126)
FREQ2	-0.280 (0.179)	-0.280 (0.179)	0.033 (0.132)	0.032 (0.132)
Rhiwbina	0.901* (0.360)	0.898* (0.360)	0.247 (0.230)	0.258 (0.232)
Llanederyn	0.790 (0.555)	0.789 (0.555)	0.554 (0.358)	0.557 (0.361)
Llanrumney	1.232* (0.526)	1.232* (0.526)	0.524 (0.348)	0.520 (0.350)
Rumney	0.840* (0.428)	0.839* (0.428)	0.247 (0.277)	0.246 (0.278)
Heath	1.588** (0.415)	1.591** (0.416)	0.529 (0.271)	0.514 (0.273)
Whitchurch	1.218** (0.409)	1.219** (0.409)	0.380 (0.270)	0.373 (0.271)
Cathays	0.978* (0.447)	0.982* (0.448)	0.542 (0.304)	0.519 (0.304)
α	0.698	0.698	1.749	1.753
λ	0.062	0.062	0.058	0.058
Log-likelihood	-1654.6	-1654.6	-1492.3	-1491.6

* significant at the 95% level; ** significant at the 99% level

Table 4.3.9: Model parameter estimates including IREP for the district store durations

Regressor Variable	Model Parameter Estimates			
	Gompertz	Gompertz	Weibull	Weibull
constant	3.574 (0.455)	3.607 (0.455)	4.097 (0.354)	4.145 (0.352)
IREP	-	-0.110 (0.116)	-	-0.146 (0.101)
NIP	-	-	0.309** (0.014)	0.309** (0.014)
DFO	0.395** (0.117)	0.391** (0.117)	0.352** (0.099)	0.351** (0.098)
LIC	0.489** (0.139)	0.491** (0.139)	0.265 (0.140)	0.255 (0.136)
AGE	0.172** (0.067)	0.171** (0.069)	0.067 (0.054)	0.066 (0.054)
MART	0.196 (0.189)	0.219 (0.193)	-0.210 (0.153)	-0.191 (0.152)
YC	0.169 (0.156)	0.165 (0.156)	-0.125 (0.120)	0.123 (0.119)
OC	0.181 (0.147)	0.181 (0.147)	-0.123 (0.136)	-0.130 (0.135)
HSZ	-0.252** (0.057)	-0.254** (0.057)	-0.320** (0.050)	-0.323** (0.050)
ADS	1.585** (0.247)	1.569** (0.247)	0.755** (0.142)	0.721** (0.143)
LOR1	0.113 (0.167)	0.103 (0.167)	0.248 (0.129)	0.250 (0.128)
LOR2	0.109 (0.188)	0.117 (0.188)	0.128 (0.146)	0.154 (0.145)
FREQ1	0.450** (0.136)	0.445** (0.132)	0.288** (0.111)	0.291** (0.113)
FREQ2	0.363* (0.147)	0.362* (0.147)	0.402** (0.121)	0.414** (0.123)
Rhiwbina	-0.711** (0.271)	-0.705** (0.269)	-0.380 (0.198)	-0.366 (0.196)
Llanederyn	0.760 (0.391)	0.759* (0.388)	0.137 (0.284)	0.151 (0.277)
Llanrumney	-0.777 (0.406)	-0.761 (0.405)	-0.629* (0.282)	-0.602* (0.279)
Rumney	-0.787** (0.308)	-0.781** (0.305)	-0.544* (0.239)	-0.555* (0.237)
Heath	-0.916** (0.308)	-0.926** (0.303)	-0.393 (0.243)	0.426 (0.239)
Whitchurch	-1.027** (0.287)	-1.044** (0.287)	-0.743** (0.246)	-0.770** (0.241)
Cathays	-0.946** (0.331)	-0.956** (0.330)	-0.614** (0.336)	-0.634** (0.232)
α/[δ]	[-0.018]	[-0.018]	1.208	1.211
λ/[λ_0]	[0.019]	[0.025]	0.007	0.007
Log-likelihood	-1906.8	-1906.3	-1707.4	-1706.4

* significant at the 95% level; ** significant at the 99% level

considered, whereas lengths of residence of 10 or more years (LOR2) becomes significant. A likelihood ratio test of the log–logistic models given in Table 4.3.8 gives a χ^2=1.4 with 1 degree of freedom, which indicates that including the influence of income reporting (IREP) results in a better fit to the local store durations at a significance level of 75%. On the other hand, coefficient results for the district store durations are similar to those obtained when income reporting (IREP) was not considered (Table 4.3.9), but a likelihood ratio test of the Weibull models given in Table 4.3.9 gives a χ^2=2.0 with 1 degree of freedom, indicating that including the effect of income reporting (IREP) gives a better fit to the district store durations at the 75% confidence level. Since explicit consideration of the effect of income reporting is seen to improve the fit of these models when the number of interpurchases (NIP) is controlled for, it seems as though inherent differences may occur between the durations observed for panellists who *did* report income status compared to those for panellists who *did not* report income status.

The second stage of the investigation of income status considered the differences between the covariates associated with *all* durations observed for panellists who *did* report income and those observed for panellists who *did not* report their incomes. Specifically, estimates for *all* durations for the entire sample (which represents 1,182 observed durations) were compared to the estimates derived for *all* durations for the panellists who *did* report income (which corresponds to a sample size of 815 observed durations). Furthermore, these results were compared to estimates obtained for *all* durations for panellists who *did not* report income, which, in turn, corresponds to a sample size of 367 observed durations. A log–logistic model was used to obtain estimates for the entire sample (n=1,182), the income reporters sample (n=815) and the income non–reporters sample (n=367) since a log–logistic model was found to best describe the durations for each of these three samples sizes.

Table 4.3.10: Model parameter estimates for *all* durations representing the entire sample (n=1182), the income status reporters sample (n=815) and the panellists who did not report income status sample (n=367)

Regressor Variable	Log-logistic Model Parameter Estimates		
	entire sample (n=1182)	income reporters (n=815)	income non-reporters (n=367)
constant	2.249 (0.302)	2.194 (0.360)	2.431 (0.603)
NIP	0.312** (0.008)	0.303** (0.010)	0.335** (0.015)
DFO	0.306** (0.077)	0.281** (0.093)	0.441** (0.152)
LIC	0.343** (0.102)	0.569** (0.127)	-0.266 (0.183)
AGE	0.111** (0.040)	0.097* (0.049)	0.166* (0.079)
MART	-0.231 (0.107)	-0.160 (0.123)	0.197 (0.275)
YC	-0.042 (0.981)	-0.120 (0.109)	0.580* (0.242)
OC	-0.123** (0.099)	-0.056 (0.123)	-0.158 (-0.175)
HSZ	-0.238** (0.037)	-0.258** (0.042)	-0.350** (0.087)
ADS	0.179** (0.132)	0.421** (0.156)	-1.373** (0.332)
LOR1	0.215 (0.107)	0.158 (0.130)	0.170 (0.247)
LOR2	0.301 (0.123)	0.285 (0.146)	0.343 (0.281)
FREQ1	0.212* (0.107)	0.312** (0.107)	0.132 (0.186)
FREQ2	0.320** (0.095)	0.365** (0.114)	0.323 (0.180)
Rhiwbina	-0.049 (0.157)	-0.133 (0.197)	0.034 (0.301)
Llanederyn	0.399 (0.231)	0.496 (0.322)	0.327 (0.393)
Llanrumney	-0.012 (0.223)	-0.311 (0.273)	1.537* (0.478)
Rumney	-0.003 (0.188)	0.149 (0.234)	-0.558 (0.345)
Heath	0.204 (0.187)	0.286 (0.225)	-0.628 (0.390)
Whitchurch	0.242 (0.190)	0.088 (0.237)	-0.815* (0.348)
Cathays	-0.045 (0.201)	-0.090 (0.247)	0.877 (0.390)
STYP	0.583** (0.070)	0.603** (0.084)	0.471** (0.122)
α	1.668	1.696	1.731
λ	0.023	0.023	0.022
Log-likelihood	-3226.6	-2203.9	-999.7

* significant at the 95% level; ** significant at the 99% level

As shown in Table 4.3.10 (page 250), some slight variation in estimated coefficients between the entire sample (n=1182) and those for the panellists who *did* report income status (n=815) occur, but, in general, these two samples appear to represent similar effects of covariates on the durations between store–type switches. For example, the number of interpurchases (NIP), deep freezer ownership (DFO), possession of a driver's license (LIC), the panellist's age (AGE), accessibility to district stores (ADS), the panellist's *perceived* rate of weekly shop visits (FREQ1 and FREQ2) and the store type (STYP) covariates are all seen to significantly increase the durations, whilst household size (HSZ) is seen to significantly decrease the durations in both of these samples (see Table 4.2.10). On the other hand, the covariate representing the presence of older children (OC) is estimated as being significant in only the entire sample (n=1182). It is possible that these results reflect the slightly greater percentage of durations observed for households with an older child in the income reporting sample (64.8%) compared with that of the entire sample (58.7%) (see Table B.3, Appendix B). However, since similar percentages for <u>most</u> of the covariates occur in both of these samples, the behavioural variation resulting from the covariates is retained, and hence the overall 'trend' in the effects of the covariates on the durations is very similar.

Alternatively, the coefficient estimates associated with panellists who *did not* report income status, (n=367), exhibit some differences when compared to the entire sample. The number of interpurchases (NIP), deep freezer ownership (DFO), the panellist's age (AGE), household size (HSZ), accessibility to district stores (ADS) and the store type (STYP) covariates are estimated as significant influences on the durations, as was found previously. However, the accessibility to district stores (ADS) covariate, which was estimated as increasing the durations in the entire sample, is seen to decrease the durations observed for the income non–reporters (see Table 4.3.10). Furthermore, the covariates representing possession of a driver's license (LIC) and the *perceived* frequency of weekly store visits (FREQ1 and FREQ2) are not estimated as significantly influencing the durations observed for the non–reporters whilst the presence of young children (YC) and both Llanrumney and Whitchurch become significant influences. These findings may result from inherent differences in the characteristics associated with the income non–reporters relative to the entire sample.

The sample representing income non–reporters appear to be biased towards higher percentages of particular covariates (see Table B.1, Appendix B). In relation to the entire sample, the income non–reporters are generally older, married, have older children, have lived in their homes for longer periods of time, tend to possess a driver's license, have larger households and have poorer accessibility to district stores. For example, over 40% of the durations observed for the non–reporters (n=367) reflect panellists who possess a driver's license whereas only 29% of the durations observed for the income reporters (n=815) are for panellists who possess a license, a figure more comparable to that seen in the entire sample (see Table B.1). Therefore, the differences between the coefficients estimated for the income non–reporters and the entire sample may simply reflect differences between the durations observed for these particular panellists. Alternatively, it is possible that the store choice behaviour process associated with the panellists who *did not* report their income status may inherently differ from the store choice behaviour process associated with the panellists who *did* report income status.

The final step in the investigation of income status concerned explicit evaluation of the influence of income status (INC) on duration for those panellists who *did* report income (ie. n=815). Therefore, in addition to the covariates examined in Section 4.3.1, two binary covariates, corresponding to income levels of £2000 to £6999 (INC1) and £10000 or more (INC2), were included in the regression portion of a log–logistic model, with income levels of £7000 to £9999 as the base category. A log–logistic specification was found to provide a better representation of *all* durations for the income reporters as well as their durations disaggregated by store type than any of the other models. Therefore, coefficient estimates for *all* durations and both the local and district store durations for the income reporters sample (n=815) using a log–logistic model were derived and these results were compared to the coefficient estimates obtained from a log–logistic model when the effect of income was not considered.

From Table 4.3.11 (page 254), the coefficients representing income status are not seen to significantly influence either *all* durations or the durations disaggregated by store type. Therefore, it appears as though, at least for the income reporters, that income status is not an important influence on durations of store choice behaviour. A likelihood ratio test of the log–logistic model including the influence of income status ($\mathscr{L}$=–2202.3) for *all* durations with that obtained when the model did not include income ($\mathscr{L}$=–2203.9, see Table 4.3.10) results in a χ^2=1.2 with 2 degrees of freedom which is not statistically significant and thus it appears as though no improvement in fit is obtained by including income status.

Similar 'trends' in the coefficient estimates for *all* durations are observed when income status is explicitly considered compared to those obtained when income status was not included (see columns 1 and 2 in Table 4.3.11). Furthermore, similar effects of the covariates on durations of local store choice occur when income status is explicitly considered compared to the results derived when income status was not specified (see columns 3 and 4, Table 4.3.11). However, the influence of covariates on durations of district store choice are slightly different when income status is explicitly considered compared to when income status is not considered. In particular, Cathays becomes significant to decreasing durations of district store choice when income status is measured (see columns 5 and 6, Table 4.3.11). It is possible that additional behavioural variation may be associated with the

Table 4.3.11: Model parameter estimates for the durations including the influence of income status

Regressor Variable	Log-logistic Model Parameter Estimates					
	all durations[1]		local store[2]		district store[3]	
INC1		-		+		-
INC2		-		-		-
NIP	+(**)	+(**)	+(**)	+(**)	+(**)	+(**)
DFO	+(**)	+(**)	+	+(*)	+(*)	+(*)
LIC	+(**)	+(**)	+(**)	+(**)	+(**)	+(**)
AGE	+(**)	+(*)	+	+	+	+
MART	-	-	-	-	-	-
YC	-	-	-	-	-	-
OC	-	-	+	-	-	-
HSZ	-(**)	-(**)	-(**)	-(**)	-(**)	-(**)
ADS	+ (*)	+(**)	-	-	+(**)	+(**)
LOR1	+	+	-	-	+	+
LOR2	+	+	+	+	+	+
FREQ1	+ (*)	+(**)	+	+	+(**)	+(**)
FREQ2	+ (*)	+(**)	+	+	+(**)	+(**)
Rhiwbina	-	-	+	+	-	-
Llanederyn	+	+	+	+	+	+
Llanrumney	-	-	+	+	-(*)	-(*)
Rumney	+	+	+	+	-	-
Heath	+	+	+	+	-	-
Whitchurch	+	+	+	+	-	-
Cathays	-	-	+	+	-	-(*)
STYP	+ (*)	+(**)				

* significant at the 95% level; ** significant at the 99% level

[1] n=815; [2] n=345; [3] n=470

socio–economic characteristics of Cathays relative to the base (category) study are Roath which may not be adequately measured by income status alone. This result may also reflect correlation between income and other covariates such as, the area of the panellist's residence (in particular Cathays) which may bias the parameter estimates. In general, however, the influence of income status does not appear to significantly effect durations of store choice behaviour for those panellists who reported income.

CHAPTER FIVE

THESIS CONCLUSIONS

This thesis began with a review of many of the developments in retailing which have led to increasingly competitive and specialized retail environments. Current retailing practices are concerned with targeting diversified and individualized markets which, consequently, has led to a need to obtain detailed and spatially disaggregate consumer behaviour information. The collection of longitudinal purchasing data using scanner panels results in extensive, spatially disaggregate and detailed purchasing histories which provides retailers with new opportunities for analyzing the behaviour patterns of different consumers and thus take on more active roles in developing successful marketing and retailing strategies. A necessary element in the use of scanner panel information, and one which forms the focus of this research, concerns the development of appropriate methodologies for analyzing this type of data.

Chapter Two provided an extensive review of existing modelling approaches to consumer behaviour. The review highlighted several approaches taken towards analyzing store choice, ie. shopping behaviour, and also approaches to the question of temporal dependence in consumer purchasing behaviour. Modelling approaches which examine spatial choice processes have tended to neglect the influence of time dependence in consumer shopping behaviour. On the other hand, studies which examine time dependence in consumer behaviour have largely considered aspatial decisions, focusing on purchases of particular brands or products. Furthermore, studies which have examined time dependence in consumer behaviour tend to make simplifying assumptions which largely fail to inherently address the dynamic nature of consumer decision processes or alternatively, assume distributional forms to represent the influence of time dependence without theoretical or empirical justification of such forms. The lack of attention to evaluation of time dependence in consumer shopping behaviour is due, in part, to the multidisciplinary nature of consumer behaviour research but also reflects the limitations of aggregate panel data previously available. This research adopted a continuous–time stochastic modelling approach to longitudinal panel data for examining time dependencies in consumer shopping behaviour and used a consumer panel data set with a high level of temporal disaggregation (ie. days).

Continuous–time stochastic process theory forms the theoretical backcloth for this thesis and this process theory distinguishes between three different sources of behavioural variation, namely heterogeneity, nonstationarity and state dependence. Although very generalized models, along the lines of those proposed by Heckman (1981a) and Tardiff (1980), consider all three sources of behavioural variation, in any particular application interest may lie in only restricted forms of such models. This restricted approach may reflect interest in specific characteristics of the behavioural process, may reflect restrictions in terms of the identifiability of models, may reflect particular constraints on the analysis (largely computational) or may reflect interest in particular model terms, such as exogenous variables, with the goal of producing estimates of individual characteristics.

The primary interest of this research concerned evaluating the distributional form of duration dependence involved in consumer store switching behaviour. Duration dependence corresponds to one type of state dependence effect and, in this thesis, duration dependence was defined as the amount of time a consumer remains loyal to one type of store before switching to another store type. It was assumed that the probability of choosing a particular type of store, with store choices limited to either district or local centre stores for purchases of the product category baked beans, depends on both the type of store visited in the preceding trip and the time elapsed since that trip. Duration dependence between different store–type switches was therefore considered to depend on both the *state* and the *timing* of previous shopping trips. In continuous–time, event–history stochastic modelling approach, the distributional form of this duration dependence can be expressed in terms of the hazard rate, where an event is synonymous with a store–type switch.

The main findings of this thesis relate to the performance of alternative event–history models in representing the duration dependence involved in consumer store switching behaviour. The use of an event–history methodology for analyzing consumer behaviour data remains largely unexplored and thus this research represents one of only two known empirical examples of this approach. This work is unique for comparing the relative performance of alternative distributional forms for describing the form of duration dependence, ie. the hazard rate. Also, this research is significant for comparing the exogenous factors associated with store switching behaviour with those associated with loyalty towards particular store types. These features make the research findings described in this thesis important contributions to the investigation of time dependencies in consumer behaviour processes.

Results indicate that a hazard rate derived from a monotonically decreasing Gompertz model best described *all* durations (ie. those associated with switching between store types) as well as the durations of district store choice, whilst a monotonically decreasing log–normal model provided the best representation of the local store durations. An exponential model consistently gave the worst fit to these durations which indicates that a constant hazard rate is inappropriate to this data. This implies that the assumption of temporal independence between successive purchases inherent in the NBD, BBD and Dirichlet 'distributional–based' models appears to be insufficient in describing the duration dependence occurring in the shopping behaviour patterns examined in this research. Furthermore, these results indicate that the distributional form of duration dependence is different for local and district store choice. Therefore, not only is duration dependence seen to be an important influence on the time between store–type switches but, this timing appears to be different for local and district store choice.

Consideration of the dynamic nature of consumer behaviour was restricted to controlling for the endogenous influence of the number of interpurchases on duration. The results indicate that the number of interpurchases is an important influence on shopping patterns. These findings provide empirical support for the notion that inventory effects, which result from purchases made on previous shopping trips, are important influences on durations between shopping trips. Hazard rate estimates show that when the number of interpurchases was included in model estimates a nonmonotonic log–logistic distribution best described *all* durations as well as the durations for local store choice. Alternatively, a monotonically increasing Weibull model was found to provide the best estimate for the district store durations. Therefore, since different distributional forms of duration dependence were derived for local and district store choice it seems as though the inventory effects associated with local store shopping trips may be different from the inventory effects occurring in district store shopping trips.

Coefficient estimates for the influence of the number of interpurchases indicates that with increasing numbers of repeat visits to a particular type of store (ie. either a local or a district store) tends to reinforce the choice of that store type for subsequent purchases, ie. thereby decreasing the hazard rate. The probability of switching from a local store to a district store was found to consistently be greater than that associated with switching from a district store to a local store. Consequently, this implies that habitual choice of district stores tends to occur for longer durations than does durations of habitual choice of local stores.

An important part of this research, and one which has significant implications for targeting marketing strategies, concerns the identification of individual characteristics which may be associated with different store–type shopping trips. Measured sources of population heterogeneity were included in model estimates by extending the hazard rate models to include a vector of exogenous covariates. Household characteristics reflecting deep freezer ownership, the age of the panellist, possession of a driver's license, household size, accessibility to district centre stores, the panellist's *perceived* 'regularity' of weekly shop visits and the *state* of the shopping trip (being either to local or district stores) were all found to be significant influences on *all* durations. These results appear to provide support for the findings of Davies and Pickles (1987), in which individuals possessing different household characteristics were found to exhibit a degree of substitution between district and local store shopping trips. In other words, these findings imply that while durations of 'loyalty' towards both district and local stores is observed, switching between store types appears to be the rule rather than the exception for this data. Furthermore, the same household characteristics which were found to be significant to *all* durations were also estimated as significant to durations of district store choice, with the exception of the panellist's age. In terms of local stores, the panellists's age, the presence of older children in the household and household size were found to be significant influences on durations of local store choice.

Therefore, particular characteristics, including the panellist's possession of a separate deep freezer and possession of a driver's license, were found to significantly increase the tendency towards district store choice but were not seen to be important to local store choice behaviour. Therefore, at this level of analysis, these two characteristics may be viewed as being specific to the choice of district stores as shopping destinations and as such, could be viewed as 'fundamental' characteristics which should be considered in retailing strategies aimed at promoting district stores. Furthermore, some of the individual characteristics associated with the tendency towards district store 'loyalty' were not seen to be important influences on durations of 'loyalty' towards local stores. Most noticeably, the panellist's age and the presence of older children in the household were not found to be significant to district store choice but was seen to significantly increase durations of local store choice. These findings imply that older panellists may be more likely to habitually shop at local stores compared to younger panellists whereas habitual choice of district stores may not be related to age structure. Moreover, the presence of older children appears to result in a greater mix of shopping trips as such households may make more 'filler' trips, supplementing inventory stocks with frequent trips to local stores. Thus the presence of older children may be an important target marketing factor which should be considered in retailing strategies geared towards promoting local stores.

It should also be noted that inclusion of exogenous covariates does not alter the distributional form of duration dependence, but may provide insight as to the more appropriate parametric forms which can be used to describe the data. In particular, the constant hazard rate of the exponential model appears to result in 'spurious' heterogeneity, providing further support for the notion that an assumption of no duration dependence is inadequate for this data.

Results from the investigation concerning the influence of income status indicate that, for panellists who reported their household income, the influence of income was not generally an important influence on *all* durations, nor the durations disaggregated by store type. However, inherent behavioural differences may exist between panellists who *did* report their income and panellists who *did not* report income status. Moreover, such differences were not adequately measured by simply including a binary covariate to represent the occurrence of income reporting. Essentially, panellists who *did not* report income were seen to have higher percentages of particular household characteristics relative to those of panellists who *did* report income.

5.1 Directions for Future Research

This analysis, not unlike many other studies of consumer behaviour which examine repeat observations, made the assumption that successive store trips made by a panellist were independent and thus, each duration contributed equally to the parameter estimates. However, it is likely that temporal (serial) correlation exits between the durations observed for a single panellist. This problem essentially becomes one of handling varying numbers of durations observed for each panellist. As a result, certain household characteristics which appeared to be important influences on shopping behaviour may not be and this variation may simply result from a bias towards certain characteristics of panellists who experienced larger numbers of durations. One method which may reduce this problem would be to consider the store choice behaviour associated with products which exhibit greater homogeneity in the purchasing rates which, in turn, may result in more equal numbers of durations observed per panellist than was found for the product category baked beans. Alternatively, the durations could be sampled at random points within an observation window which could ensure the same number of durations for each panellist. Another option would be to explicitly model any dependency between durations by incorporating a measure(s) which accounts for the influence of previous durations on current store choice behaviour.

It would be interesting to compare the duration dependence occurring in the store choice behaviour for different products with the results obtained in this research. It is likely that products with different characteristics, such as different inventory effects, may exhibit alternative forms of duration dependence associated with store choice behaviour. Furthermore, it would be interesting to disaggregate the number of store choices from the binary situation examined in this research to a polytomous choice situation in which multiple store alternatives could be defined as being specific to each panellist. For example, the five most frequently visited stores could be used to define the choice set for each panellist and then comparisons of the duration dependence for alternative products could be conducted.

The appropriateness of the parameters estimates obtained in this analysis could be evaluated using the model residuals. This method is similar to that used in ordinary linear regression and can be used to examine both censored and non–censored data for any of the event–history models examined in this analysis. Generally, for each observation, i, with covariates $\mathbf{x}_i$, a residual can be defined such that $\hat{r}_i = \Lambda\ (t \mid \beta_i) = -\ln \hat{S}_i(t \mid \beta_i)$, where $\hat{\Lambda}\ (t \mid \beta_i)$ is the estimated integrated hazard rate containing information on the parameters at time t. The reader is referred to Kalbfleisch and Prentice (1980) and Blossfeld et al. (1989) for the residual equations corresponding to the continuous–time event history models examined in this thesis. If the estimated model is appropriate to the data the calculated residuals should, when plotted on a logarithmic scale, yield an approximately straight line with slope –1. However, further investigation as to the properties of residuals is needed before their usefulness to the evaluation of event–history models can be fully advocated. For instance, Kalbfleisch and Prentice (1980) note that if the model assumptions are violated, it is not apparent what type of deviations would be expected in the residuals, nor is it known to what extent agreement with the anticipated line should be expected. Given this, residual analysis appears to hold promise for evaluating the findings described in this thesis but remains an avenue to be explored in future research.

Another issue concerning the adequacy of model specification derives from the efficiency of the estimated parameter vector (ie. $\hat{\beta}$) in representing the influence of measured sources of population heterogeneity. It is possible that correlation exists between the covariates which could potentially have resulted in biased coefficient estimates. One method of evaluating the covariance associated with $\hat{\beta}$ is derived from using the main diagonal elements of the second derivative of the log–likelihood function (ie. the second derivative of the Fischer information matrix). These elements are asymptotically distributed and thus the hypothesis of no correlation between covariates can be statistically evaluated from a central χ^2 distribution (see Kalbfleisch & Prentice, 1980; Blossfeld et al., 1989 for the details of this method and discussion of alternative methods). Possible correlation between covariates was not actively pursued in this research, as the primary focus of this work concerned the application of an event–history methodology, and would constitute a more important topic which would need to be considered in the development towards forecasting models of consumer shopping behaviour.

Lastly, the parameter estimates derived in this study could potentially be biased due to unobserved sources of population heterogeneity. Recall from Section 2.4.2 that neglecting the influence of unobserved heterogeneity may lead to an apparent or 'spurious' duration dependence. One alternative could be to adopt a nonparametric fixed–effects approach which essentially, would consist of specifying a constant error terms for each duration representing a particular panellist's unobserved heterogeneity (see Reader, 1988). The influence of unobserved heterogeneity on the distributional form of duration dependence has not been examined in the consumer behaviour literature and provides an important research question to be left for future research.

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APPENDIX A: THE CARDIFF CONSUMER PANEL

Figure A.1: A shop diary page

(source: Guy et al., 1983:14)

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		

Figure A.2: The initial questionnaire: household information

(source: Guy et al., 1983:234)

RESEARCH & MARKETING
(WALES & THE WEST) LIMITED
389 NEWPORT ROAD
CARDIFF CF2 1RP

4	0	4	0
Job Number			

Code Number

CARDIFF HOUSEHOLD SURVEY - J.4040

(Cols 1-7)

ADDRESS: ______________________

HOUSEHOLD NUMBER: (Col 8)

INTERVIEW THE PERSON IN THE HOUSEHOLD WHO IS RESPONSIBLE FOR BUYING MOST OF THE GROCERIES AND PROVISIONS EATEN BY THE HOUSEHOLD.

Good morning/afternoon/evening. I'm working for Research & Marketing Ltd, who are doing a survey of household shopping in this area.

Q.1. About how many times a week do you normally buy groceries? (9)

Once a week or less often	1
Twice a week	2
Three times a week	3
Four times a week	4
Five times a week	5
Six or seven times a week	6
Varies	0

Q.2. How many cars and vans are normally available for use by you or members of your household (other than visitors) ?

(Include any car or van provided by employers if normally available for use by members of the household but exclude vans used solely for the carriage of goods) (10)

One	1
Two	2
Three	3
Four or more	4
None	0

Q.3. Do you have a paid job ? (11)

Yes: Work full-time (30 hrs or more per week)	1
Yes: Work part-time (less than 30 hrs per week)	2
No: Not working/retired	3

CLASSIFICATION SECTION

SEX OF RESPONDENT (12)

Male	1
Female	2

AGE OF RESPONDENT (13)

16-24	1
25-34	2
35-44	3
45-54	4
55-64	5
65 and over	6

HOUSEHOLD COMPOSITION (14-19)

No. of children 0-4 years ____
No. of children 5-15 years ____
No. of adults 16-44 years ____
No. of adults 45-64 years ____
No. of adults Over 64 years ____
TOTAL in household (including respondent) ____

WORKING STATUS OF ADULTS IN H/H

(Those aged 16 and over)

Number of adults in household: (20-23)

Working full-time (30 hrs or more per week) ____
Working part-time (Less than 30 hrs per week) ____
Not working/retired ____
TOTAL adults ____

RESPONDENT'S NAME

Mr/Mrs/Miss: ______________________

Thank respondent and ask if he/she is willing to become a panel member, completing a shopping diary every week. (24)

Interested in completing diaries; code number (top right of this page) written on contact record sheet	1
Will not be completing diaries	2

Interviewer's Name: ______________________

Date of interview : ______________________

Figure A.2 continued...

Now I would like to ask you some general questions about your household.

Q.2) How long have you been living at this address ?

Less than three months	1
3 months but less than 6 months	2
6 months but less than 1 year	3
1 year but less than 2 years	4
2 years but less than 3 years	5
3 years but less than 10 years	6
10 years or more	7
Can't remember	8

Q.3a) Do you have a refrigerator ?

Yes	1
No	2

b) Do you have a fridge freezer ?

Yes	1
No	2

c) Do you have a separate deep freeze ?

Yes	1
No	2

Q.4) **How many cars and vans are normally available for use by you or members of your household (other than visitors) ?**

(Include any car or van provided by employers if normally available for use by members of the household but exclude vans used solely for the carriage of goods)

One	1	→ Q5a)
Two	2	→ Q5a)
Three	3	→ Q5a)
Four or more	4	→ Q5a)
None	0	→ Q.6

IF CAR OR VAN AVAILABLE: OTHERS GO TO Q. 6

Q.5a) Do you have the use of any of these vehicles when shopping: sometimes, all the time or never ?

[Code 'Yes' if the panellist uses the vehicle/s as driver or passenger]

Yes; all the time	1
Yes; sometimes	2
No; never	3

b) Do you, yourself, hold a current full driving licence ?

Yes	1
No	2

Figure A.2 continued...

ASK ALL

Q.6) How old were you when you finished your full-time education?

14 years or under	1
15	2
16	3
17	4
18	5
19 or older	6
Still studying	7
Never at school	8
Can't remember	9

Q.7a) Did you pass any recognised examinations as part of your education or training ?

Yes	1	→ b)
No	2	→ Q.8
Can't remember	3	→ Q.8

IF YES: OTHERS GO TO Q. 8

b) What was the last examination you passed ?

University degree/Dip.Ed.or above	1
Professional Institute's final exam/Higher National Certificate	2
Teachers Training Certificate	3
G.C.E.'A' level/Professional Institute's Intermediate Exam/ S.R.N.	4
G.C.E. 'O' level/Secretarial Diploma/Ordinary National Certificate	5
Other (please specify) ______	6
Can't remember	7

ASK ALL

Q.8) Did you complete a full industrial apprenticeship ?

Yes	1
No	2

Q.9) Sex of panellist:

Male	1
Female	2

Q.10) Age of panellist:
(Estimate if refuses to say)

16-24	1
25-34	2
35-44	3
45-54	4
55-64	5
65-74	6
75 and over	7

Fiure A.2 continued...

Q.11) Marital status of panellist:

Married	1	
Single	2	
Widowed/divorced/separated	3	

Q.12a) Do you have a paid job ?

Yes: Work full-time (30 hrs or more per week)	1	→ b)
Yes: Work part-time (less than 30 hrs per week)	2	→ b)
Student (full-time)	3	→ Q.13
Wholly retired/other not working	4	→ Q.13

IF WORKING FULL OR PART-TIME : OTHERS GO TO Q.13

b) Occupation details of panellist (WRITE IN BELOW)

JOB TITLE: ______________________

POSITION/RANK/GRADE: ______________________

WORK-PLACE (name & address) ______________________

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(52 - 53)

(54 - 55)

ASK ALL

Q.13) Code relationship of panellist to **Head of Household**

Respondent is Head of Household	1	→ Q.15
Wife	2	→ Q.14
Son/daughter	3	→ Q.14
Other relative	4	→ Q.14
Friend/unrelated	5	→ Q.14

IF PANELLIST IS NOT H. OF H. : OTHERS GO TO Q. 15

Q.14) Occupation details of Head of Household (WRITE IN)

JOB TITLE: ______________________ (Give last job if unemployed or wholly retired)

POSITION/RANK/GRADE: ______________________

WORK-PLACE (name & address) ______________________

FOR OFFICE USE ONLY

PLEASE TURN OVER PAGE

Figure A.2 continued...

ASK ALL

SHOW CARD B

Q.15) **Could you please tell me, using this card, which of these comes closest to the total income of your household from all sources, before tax and insurance is deducted.**

I only want to know the letter to the left of the one which is closest.

Letter	Weekly	Monthly	Annual	
G	Under £20	Under £84	Under £1000	1
F	£20 - £39	£84 - £167	£1000 - £1999	2
E	£40 - £58	£168 - £250	£2000 - £2999	3
D	£59 - £97	£251 - £417	£3000 - £4999	4
C	£98 - £135	£418 - £584	£5000 - £6999	5
B	£136 - £192	£585 - £834	£7000 - £9999	6
A	£193 - £289	£835 - £1249	£10000 - £14999	7
X	£290 +	£1250 +	£15000 +	8
			Don't know	9
			Refused to say	0

CLOSE INTERVIEW, THANK PANELLIST AND SAY THAT HIS/HER NUMBER WILL NOW BE ENTERED IN THE PRIZE DRAW. THERE WILL BE ONE WINNER OF £3 IN EACH OF THE 15 AREAS OF CARDIFF ON THE PANEL AND THIS WILL BE THE FIRST OF SEVERAL SIMILAR DRAWS.

INTERVIEWER DECLARATION:

I declare that this interview has been conducted with the person named on the front page at his/her address as instructed.

Date of interview: ____________________ 1982

Interviewer's signature: ____________________

Figure A.3: The final questionnaire: consumer attitudes (numbers in parentheses reflect the number of respondents)

Research & Marketing
(Wales & The West) Ltd.,
389 Newport Road,
CARDIFF CF2 1RP

HOUSEHOLD SHOPPING DIARY - J4040

SHOPPING ATTITUDES SURVEY

INTERVIEW EACH OF YOUR PANELLISTS

(Cols. 1-4 BLANK)

NAME OF PANELLIST: ______________ PANELLIST NUMBER: (Cols. 5-7)

ADDRESS: ______________ QUESTIONNAIRE ORDER: (8) 2

SHOW CARD A

Q.1) I am going to read out some comments that might be made about shopping.

Would you please tell me, using this card, how strongly you agree or disagree with each comment.

(READ OUT)

	AGREE STRONGLY	AGREE	NEITHER AGREE NOR DISAGREE	DIS-AGREE	DIS-AGREE STRONGLY	DON'T KNOW
I usually try hard to look for bargains	1 (69)	2 (233)	3 (44)	4 (107)	5 (6)	9 (2)
The way a person shops for the household groceries is a good indication of how capable they are all round	1 (22)	2 (251)	3 (69)	4 (82)	5 (18)	9 (9)
I like shopping because it gets me out of the house	1 (27)	2 (156)	3 (39)	4 (177)	5 (54)	9 (2)
I think you get better quality meat in a butcher's shop than in a supermarket	1 (125)	2 (192)	3 (51)	4 (73)	5 (7)	9 (3)
I find that shopping is a nuisance and I like to get it done as quickly as possible	1 (64)	2 (154)	3 (50)	4 (165)	5 (17)	9 (1)
I think you get better quality fruit and vegetables in a green-grocer's shop than in a supermarket	1 (104)	2 (230)	3 (45)	4 (61)	5 (5)	9 (6)
I find shopping for my groceries very tiring	1 (25)	2 (166)	3 (68)	4 (181)	5 (10)	9 (1)
I try to avoid walking for more than five minutes with a bag of shopping	1 (34)	2 (165)	3 (38)	4 (182)	5 (29)	9 (3)
I usually do my grocery shopping on a journey when I do other errands or other shopping	1 (11)	2 (208)	3 (31)	4 (187)	5 (13)	9 (1)
I prefer to buy meat in a super-market because you can take your time choosing exactly what you want	1 (10)	2 (96)	3 (39)	4 (219)	5 (83)	9 (4)

(based on: Guy et al., 1983:236–41)

Figure A.3 continued...

	AGREE STRONG-LY	AGREE	NEITHER AGREE NOR DISAGREE	DIS-AGREE	DIS-AGREE STRONGLY	DON'T KNOW
Shopping for groceries is usually enjoyable	1 (5)	2 (159)	3 (55)	4 (182)	5 (48)	9 (2)
The convenience of local shops is worth the extra it can cost	1 (21)	2 (262)	3 (50)	4 (103)	5 (11)	9 (4)
I think the grocery shops in Cardiff are excellent	1 (35)	2 (262)	3 (88)	4 (53)	5 (5)	9 (8)
When I am shopping I am usually in a hurry	1 (47)	2 (168)	3 (29)	4 (191)	5 (14)	9 (2)
I like to buy really fresh bread	1 (220)	2 (199)	3 (18)	4 (10)	5 (1)	9 (3)
Chain stores and supermarkets make for better grocery shopping all round	1 (36)	2 (315)	3 (44)	4 (46)	5 (8)	9 (2)
I find the staff more friendly in small shops	1 (36)	2 (243)	3 (70)	4 (90)	5 (3)	9 (9)
I prefer to shop at the 'small man' type of shop	1 (11)	2 (169)	3 (86)	4 (252)	5 (229)	9 (4)
I don't mind going out of my way to get to better shops	1 (26)	2 (257)	3 (48)	4 (114)	5 (3)	9 (3)
I think that supermarkets are cleaner than small food shops	1 (18)	2 (149)	3 (119)	4 (139)	5 (11)	9 (15)
I always try to buy good quality food, even if prices are higher	1 (60)	2 (291)	3 (40)	4 (55)	5 (3)	9 (2)
I usually do a lot of comparing of prices for ordinary food purchases	1 (65)	2 (198)	3 (39)	4 (133)	5 (16)	9 (1)
There's not much difference between shops these days	1 (5)	2 (170)	3 (28)	4 (194)	5 (45)	9 (9)
Getting shopping done quickly is very important to me	1 (54)	2 (197)	3 (39)	4 (153)	5 (7)	9 (1)
I like to buy all my groceries at one shop, rather than shop around	1 (38)	2 (169)	3 (24)	4 (194)	5 (20)	9 (1)
I would prefer to do all my shopping just once a week	1 (37)	2 (188)	3 (23)	4 (186)	5 (15)	9 (2)
Given a choice between good shops and good parking facilities, I would choose to shop where there is better parking	1 (21)	2 (131)	3 (95)	4 (171)	5 (22)	9 (11)
Going grocery shopping gives you the chance to meet friends and acquaintances	1 (15)	2 (175)	3 (47)	4 (183)	5 (30)	9 (1)

Table A.1: Characteristics of the Cardiff Consumer Panel

Variable	No. of Panellists (%)	Code*
Length of Residence:		
0 < 3 months	1 (0.2)	1
3 - 5 months	5 (1.1)	2
6 < 12 months	23 (5.1)	3
1 < 2 years	23 (5.1)	4
2 < 3 years	30 (6.7)	5
3 < 10 years	117 (25.9)	6
10 + years	249 (55.2)	7
unknown	3 (0.7)	9
Refrigerator Ownership:		
yes	442 (98.0)	0
no	8 (1.8)	1
unkown	1 (0.2)	9
Fridge with Freezer Owned**:		
no	297 (65.9)	0
yes	151 (33.5)	1
unknown	3 (0.7)	9
Deep Freezer Owned**:		
no	245 (54.3)	0
yes	204 (45.2)	1
unknown	2 (0.4)	9
No. of Cars (Vans) Owned:		
none	136 (30.2)	0
one	241 (53.4)	1
two or more	73 (16.2)	2
Use of Car for Shopping:		
never	166 (36.8)	0
sometimes	151 (33.5)	1
all the time	134 (29.7)	2
Drivers Licence:		
no	289 (64.1)	0
yes	162 (35.9)	1
Gender:		
female	423 (93.8)	1
male	28 (6.2)	2

Table A.1 continued... Variable	No. of Panellists (%)	Code
Education:		
University degree	22 (4.9)	1
College training	19 (4.2)	2
'A' levels	23 (5.1)	3
'O' levels	76 (16.9)	4
other	54 (12.0)	5
unkown	19 (4.2)	6
no exam passed	238 (57.8)	7
Age:		
16 - 24 years	17 (3.8)	1
25 - 34 years	134 (29.7)	2
35 - 44 years	82 (18.2)	3
45 - 54 years	89 (19.7)	4
55 - 64 years	82 (18.2)	5
65 - 74 years	41 (9.1)	6
75 + years	6 (1.3)	7
Marital Status:		
single (divorced, widowed)	86 (19.1)	0
married	365 (80.1)	1
Employment Status:		
not employed	246 (54.5)	0
employed part-time/student	136 (30.2)	1
employed full-time	69 (15.3)	2
Panellist is:		
head of household	92 (20.4)	1
wife of head of household	345 (76.5)	2
son, daughter	5 (1.1)	3
other relative	4 (0.9)	4
unkown	5 (1.1)	9
No. of Children: 0 - 4 years:		
none	364 (80.7)	0
one	87 (19.3)	1
No. of Children: 5 - 15 years:		
none	249 (55.2)	0
one	202 (44.8)	1

Table A.1 continued... Variable	No. of Panellists (%)	Code
Household Income:		
£0 - 1999	12 (2.7)	1
£2000 - 4999	112 (24.8)	2
£5000 - 6999	58 (12.9)	3
£7000 - 9999	64 (14.2)	4
£10000 - 14999	44 (9.8)	5
£15000+	14 (3.1)	6
unkown	147 (32.6)	9
Household Size:		
1 person	33 (7.3)	1
2 person	113 (25.1)	2
3 person	90 (20.0)	3
4 person	124 (27.5)	4
5 person	58 (12.9)	5
6 person	29 (6.4)	6
7 person	4 (0.9)	7
Frequency of Weekly Shopping:		
irregular	22 (4.9)	0
once	105 (23.2)	1
twice	86 (19.1)	2
three times	72 (16.0)	3
four times	59 (13.1)	4
five times	15 (3.3)	5
six or more times	92 (20.4)	6
Accessibility to Local Stores:		
poor	241 (53.4)	0
good	210 (46.6)	1
Accessibility to District Stores:		
poor	297 (65.9)	0
good	154 (34.1)	1

* Codes reflect values assigned in this study

** Detailed inspection of overlap among these responses reveals that 321 panellists owned some type of freezing equiptment

Table A.2: The number of panellists purchasing each of the product categories examined in the Cardiff Consumer Panel (note: product category number 21 corresponds to baked beans)

Product Category*	Number of Purchases									
	0	1-5	6	7-11	12	13-17	18	19-23	24	25+
1	183	162	12	32	9	26	5	16	2	4
2	17	161	24	97	12	57	9	46	9	19
3	11	165	42	116	14	57	5	27	3	11
4	3	124	28	111	16	71	15	54	8	21
5	147	242	14	34	1	11	0	2	0	0
6	194	169	10	38	1	12	2	13	2	10
7	89	205	30	59	14	36	7	8	0	3
8	57	240	26	64	7	32	5	13	1	6
9	13	52	12	79	12	85	15	78	22	83
10	0	1	0	0	1	10	0	14	5	420
11	1	10	5	25	5	43	12	65	16	269
12	14	66	14	57	23	66	9	41	8	153
13	26	99	12	48	3	46	13	50	7	147
14	199	204	12	24	3	7	0	1	0	1
15	38	196	32	98	13	43	7	15	6	3
16	5	65	9	72	14	80	17	79	21	89
17	140	214	21	48	5	15	1	6	0	1
18	41	226	21	101	5	33	6	16	0	2
19	241	183	12	12	2	0	0	1	0	0
20	42	137	21	109	18	49	13	39	4	19
21	27	87	23	76	17	58	14	65	15	69
22	176	155	15	53	9	20	2	12	1	8
23	215	196	9	24	1	3	0	1	2	0
24	81	216	22	68	11	30	4	8	5	6
25	25	180	25	102	16	39	9	27	4	24
26	71	205	18	68	16	37	8	19	5	4

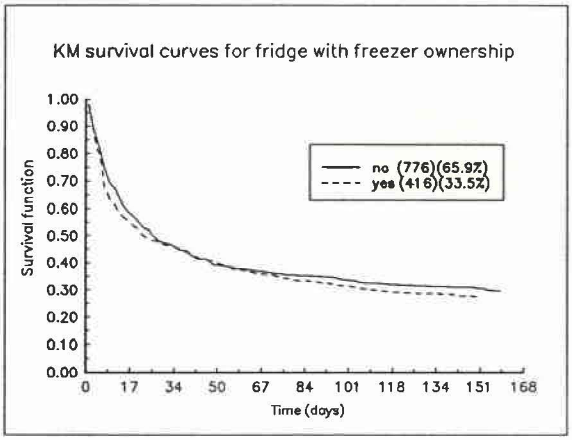
Table A.2 Continued...										
Product Category	Number of Purchases									
	0	1-5	6	7-11	12	13-17	18	19-23	24	25+
27	70	174	24	87	6	38	3	29	2	18
28	201	193	8	33	4	7	0	2	2	1
29	56	174	34	86	11	36	6	26	4	18
30	15	78	13	75	16	77	17	73	21	66
31	274	125	9	16	4	9	4	4	2	4
32	254	163	3	21	0	1	0	4	0	5
33	1	5	0	6	0	7	6	17	6	403
34	15	110	24	106	19	58	12	50	5	52
35	33	145	11	85	17	55	12	43	0	50
36	2	23	7	23	4	39	3	55	11	284
37	256	181	5	7	0	2	0	0	0	0
38	54	184	21	89	16	47	7	26	1	6
39	97	202	22	78	5	29	2	10	1	5
40	25	69	20	66	12	58	16	71	20	94
41	53	89	7	41	6	43	8	84	24	96
42	63	149	10	54	8	22	8	20	2	115
43	17	98	12	74	14	71	11	54	11	89
44	1	14	4	46	10	82	12	90	21	171
45	37	145	25	86	16	52	9	43	5	33
46	140	229	17	34	2	13	3	8	0	5
47	6	24	4	53	5	55	25	96	22	161
48	6	30	8	50	12	49	14	64	8	210
49	29	162	24	95	14	56	15	28	7	21
50	7	63	12	74	7	76	15	69	20	108
51	4	13	6	31	5	50	11	53	10	268

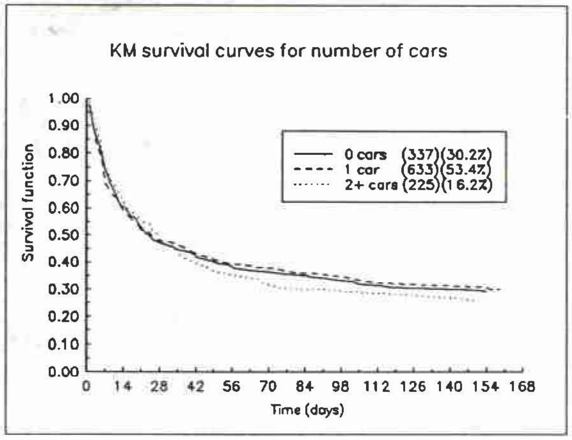
Table A.2 Continued...										
Product Category	Number of Purchases									
	0	1-5	6	7-11	12	13-17	18	19-23	24	25+
52	15	128	24	113	20	53	12	46	4	36
53	131	220	13	35	5	17	1	23	0	6
54	40	201	23	82	18	53	3	19	5	7
55	123	193	17	59	10	23	2	18	1	5
56	126	204	23	58	4	27	2	6	1	0
57	59	166	30	77	8	49	10	30	7	15
58	241	178	9	15	2	3	1	2	0	0
59	351	92	1	3	0	2	0	1	0	1
60	209	196	14	15	2	7	2	6	0	0
61	10	76	17	96	12	70	10	92	17	51
62	17	70	11	76	14	64	10	49	8	132
63	84	159	23	57	13	33	14	30	5	33
64	3	74	17	110	23	103	10	50	13	48
65	35	224	35	95	11	33	4	10	1	3
66	386	35	3	5	1	9	2	0	1	9
67	21	60	11	74	14	44	5	46	6	170
68	151	198	16	51	5	14	2	8	0	6

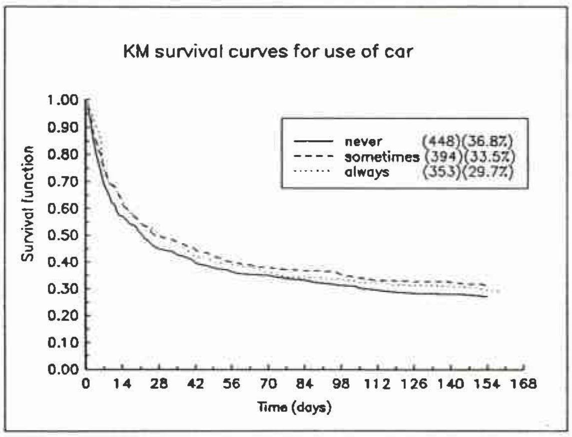
* Refer to Figure A.1 for description of the product categories

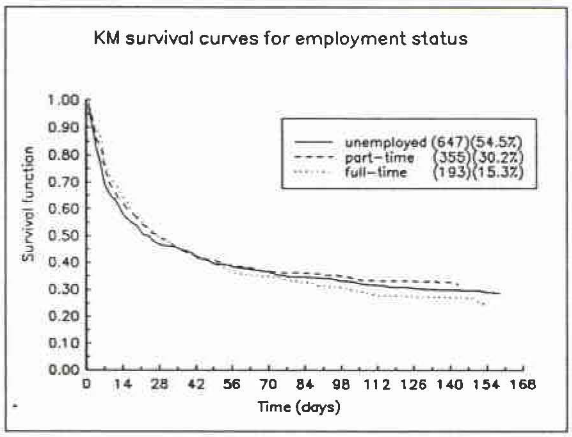
APPENDIX B: ANALYSIS FINDINGS

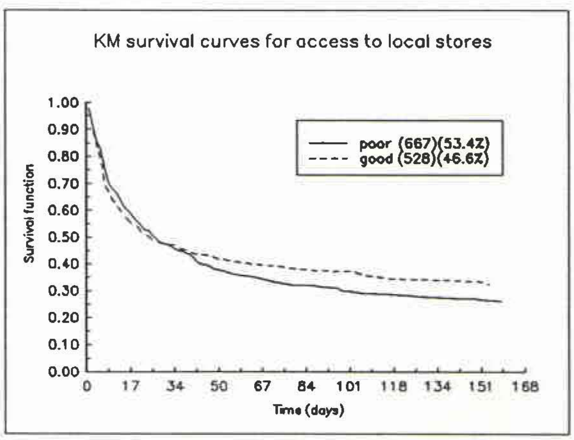
Figure B.1: KM survival curves for the variables found to not likely influence the duration between store–type switches











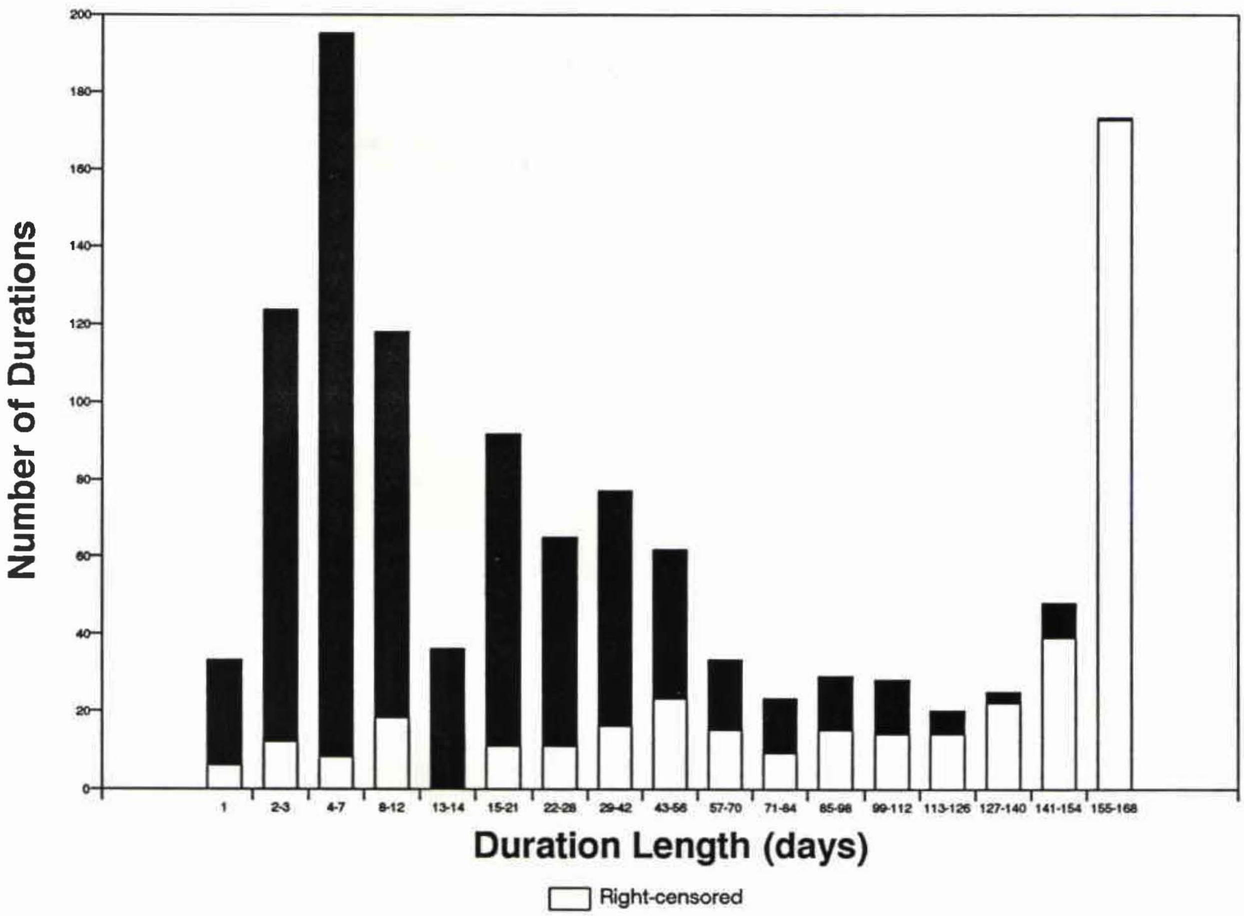


Figure B.2: Distribution of the number of durations observed for each duration length

Table B.1: Percentages of the observed durations associated with the household characteristics for the entire data set (n=1182), income reporters (n=815) and income non-reporters (n=367)

Household Covariate Category†		Percentage of Observed Durations		
		entire sample (n=1182)	income reporters (n=815)	income non-reporters (n=367)
DFO:	0	60.0	60.5	58.9
	1	40.0	39.5	41.4
LIC:	0	67.3	71.3	58.6
	1	32.7	28.7	41.4
AGE:	1	4.7	6.1	1.6
	2	37.8	42.8	26.7
	3	19.3	19.3	19.4
	4	20.7	14.0	35.7
	5	13.0	12.6	13.9
	6	4.2	5.0	2.5
	7	0.2	0.1	0.3
MART:	0	14.2	16.3	9.5
	1	85.9	83.7	90.5
YC:	0	77.3	73.9	85.0
	1	22.7	26.1	15.0
OC:	0	41.3	35.2	54.8
	1	58.7	64.8	45.2
HSZ:	1	3.6	4.5	1.4
	2	15.7	14.2	18.8
	3	19.4	17.3	24.0
	4	30.2	25.9	39.8
	5	16.8	18.2	13.6
	6	12.6	17.2	2.5
	7	1.9	2.7	0.0
ADS:	0	76.2	73.6	82.0
	1	23.8	26.4	18.0
LOR1: (3-10 years)	0	66.3	61.8	76.3
	1	33.7	38.2	23.7
LOR2: (10+ years)	0	52.3	57.9	39.8
	1	47.7	42.1	60.2
FREQ1: (1-2/week)	0	62.5	62.3	62.9
	1	37.5	37.7	37.1
FREQ2: (3-5/week)	0	67.8	68.5	66.2
	1	32.2	31.5	33.8
Rhiwbina:	0	78.9	83.2	69.2
	1	21.1	16.8	30.8
Llanederyn:	0	94.1	94.7	92.6
	1	5.9	5.3	7.4
Llanrumney:	0	90.4	90.8	89.7
	1	9.6	9.2	10.3
Rumney:	0	87.1	87.9	85.3
	1	12.9	12.1	14.7
Heath:	0	87.2	85.5	91.0
	1	12.8	14.5	9.0
Whitchurch:	0	83.4	81.4	88.0
	1	16.6	18.7	12.0
Cathays:	0	84.4	81.7	90.2
	1	15.6	18.3	9.8

† covariate categories correspond to those given in equation 4.1.7.