
PRIVATE LABEL BUYING BEHAVIOUR

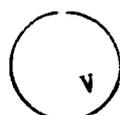
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ABSTRACT

This is an empirical study of how people buy private labels as compared with traditional branded goods in the UK packaged grocery market. The emphasis is very much on describing buying patterns rather than attempting to explain why they occur. Private labels are lines which are exclusive to a particular retailer.

An empirically derived theory of buyer behaviour is drawn upon. Two stochastic models, the Negative Binomial Distribution (NBD) and Dirichlet models describe buying behaviour and provide norms against which private label buying patterns are compared. Panel data for five product fields and two regions are analysed.

Private label buying patterns are compared with those for brands, and with theoretical predictions. Various measures of buyer behaviour are calculated; the numbers buying and the rate at which they buy; then how people buy from one time period to another; then the distribution of light and heavy buyers across the population; and finally we examine how people spread their purchases across the product field. Together, these measures provide a detailed picture of sales, and enable us to focus on issues such as private label proneness.

The analyses consists of four parts. First, we explore regularities of private label buying behaviour. However, before we can interpret the results, we have to explain a consistent deviation from the model which occurs because private labels suffer from limited availability in comparison to the average brand. This is accounted for by examining purchasing at the within store-chain level where brand and private label buying patterns are compared. Finally, private label proneness is explored by examining how people buy across two product fields.

Though there are many differences between brands and private labels, on the whole they are bought in much the same way. There are some interesting differences; private labels achieve higher within-store market shares than the average brand and are successful in this respect; there is a tendency for people having bought private labels in one product field, to be slightly more inclined to then buy them in another. Thus an indication of proneness to private labels generally rather than to specific store's private labels.

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- 11 Uncles, M.D. and Ellis, K., (1989), Own Labels : Beliefs And Reality, in Retail And Marketing Channels : Economic And Marketing Perspectives On Producer -Distributor Relationships, edited by Pellegrini, L. and Reddy, S.K., p 274-286.
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* for Andrew *

PART 1 - METHODOLOGY

CHAPTER 1 - INTRODUCTION

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CHAPTER 1 : INTRODUCTION

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1.1 INTRODUCTION

The study of consumer purchasing of packaged groceries has made significant advances in both theoretical development and practical application over the last few decades. However, most of this has been primarily concerned with the purchasing of manufacturer brands and to a lesser extent store choice. Relatively little emphasis has been given to the interaction of the two which is manifest, for example, in the choice of retailers' private labels, which is the focus of this thesis.

Private labels in the grocery sector are lines which are exclusive to a particular retailer; they receive little direct advertising support in comparison to brands; are normally sold at a lower price than brand leaders; and are generally produced by manufacturers already supplying branded goods.

Of those studies which do focus on private label purchase behaviour, most are concerned with how their buyers differ from those of brands on a variety of demographic and socio-economic characteristics, with a view to identifying a market segment for the retailer to target (Livesey and Lennon 1978, Retail Business 1971, JWT 1970, Frank and Boyd 1965). Few studies have attempted to throw light on how consumers make purchases of a particular private label at a retail chain, let alone determine if there exists any regularity in their purchase patterns. Nor are there any large-scale systematic empirical studies which focus on private labels.

The traditional emphasis on brand choice is understandable, especially during the period when manufacturers held enormous power vis-a-vis a fragmented retail industry. However, with the rise of retail power over the last 20 years, and the fact that private labels now play a central role in retail strategy and account for over a quarter of the UK packaged grocery market, the emphasis requires updating somewhat.

Today, the balance of power rests firmly with the retailer and the largest three account for roughly half of UK grocery sales. For example, the retailer can refuse to stock a manufacturer's product if the terms are less favourable than he wishes; he can also use private labels to compete directly with the manufacturer's brand. The manufacturer might therefore suffer from having the availability of his brand greatly reduced, as well as having to compete in often unfavorable conditions with the retailer's private label.

It is therefore appropriate that greater emphasis should now be given to understanding how people buy private labels and whether they do so in the way retailers strategic use of them implies. This is what the thesis is about. We examine: how people buy private labels so as to establish some norms of private label buying behaviour; whether people buy them in a way which differs from branded goods; and whether private labels provide the retailer with anything more in respect of buying behaviour than does an ordinary brand.

We draw on an extensive body of empirical research on brand buying behaviour which details how people buy brands in a variety of product fields, and use two stochastic models to describe consumer buying patterns. These provide the analytical framework within which our study on private labels is undertaken.

Not only does the study provide an empirical overview on how private labels are bought, it will contribute to a better and fuller understanding of buyer behaviour in general. It will also raise issues on such topics as branding, advertising and loyalty; and will provide retailers with information on private label purchasing patterns, which they can then take into consideration when formulating their strategies.

This introduction sets the context within which the analyses are undertaken and results interpreted. The modern retail scene is briefly reviewed with an outline of how private labels are used in retail strategy. Then we introduce the empirically derived theory of buyer behaviour which forms the lynch-pin of the thesis. Finally, the thesis structure is detailed with a short summary of the contents of each chapter.

1.2 PRIVATE LABEL STRATEGY IN GROCERY RETAILING

To appreciate how and why retailers use private labels, some knowledge of their background and the nature of their current operating environment is necessary. A brief resume of the key issues and influences that have led to the modern retail scene is now provided. (For a more detailed account see Wrigley 1988 Chapter 1.)

1.2a Retail Development and Change

Modern retailing bears little resemblance to that of 20 years ago. Environmental changes have provided retailers with opportunities which they have seized and used effectively to their advantage. The rise of multiple retailing, alongside the relative erosion of manufacturer power, has greatly altered the balance of power in the industry.

The rise in retail concentration has perhaps had the most influence on retailing (Akehurst 1983, Davies et al 1985, Rushton 1982, Cotterill 1986). Traditionally the manufacturer was the dominant partner who, using the power of his consumer franchise (developed and maintained by heavy advertising), could dictate terms to a weaker and more fragmented retail trade. Today the balance of power rests firmly with the retailer. Multiples (retailers with 10 or more outlets) have some 70% of the packaged grocery market (AGB 1988) and consequently command enormous buying power.

This change was initiated in the 1960's when new entrepreneurial management began to see both growth and profit opportunities for themselves in such things as buying, warehousing, store size and location. Up until 1962, the Restrictive Trade Practices Act (1976) stated that, "A manufacturer has the right to fix the price at which his goods are sold to the public", and a manufacturer could take price cutters to court. The abolition of Resale Price Maintenance in 1962 then provided retailers with the necessary flexibility to run their operations more profitably.

Capitalising on the abolition of Resale Price Maintenance retailers began to secure private labels contracts with some manufacturers who were already supplying them with branded goods. Initially these were cheap, inferior goods selling at prices well below those for brands. As retailer competition became more quality based, private labels started to be used to make a quality statement about the store and to help differentiate themselves from the competition. Private labels were upgraded; they were given increasing amounts of prime shelf space (Wray 1983), extensive in-store promotions and improved product quality and packaging. Indeed, today they are indistinguishable from brands in many respects.

There have been numerous repercussions from these developments:

Manufacturer margins have come under increasing pressure in order to meet retailer requirements for discounts. A 1981 Monopolies and Mergers Commission report surveyed 12 major grocery manufacturers supplying a range of nationally advertised brands. The top four multiples were shown to pay 1.5% less than the next ten, who in turn paid 2% less than the rest of the trade. Manufacturers are also under increasing pressure to undermine their own brand franchises by supplying private labels. Whitworth, for example, had 73% of the dried fruit

market in 1973 and was brand leader. Now although 70% of the market is private label, the dominant supplier ironically, is still Whitworth. The fear of delisting and the possibility of a competitor gaining a cost advantage by securing a contract forces many manufacturers to oblige.

Competition within the retail trade has intensified forcing retailers to become more efficient in terms of attracting and retaining customers. Free parking, on-site petrol stations and private labels have been used to secure a competitive advantage. Image related media campaigns have also been used. Unfortunately for the retailer, such offerings are often easily and quickly copied by their competitors.

Out-of-town hypermarket developments along with the closure of smaller more costly stores will accelerate in the continued drive for efficiency. Central warehousing has continued to grow because they provide the retailer with more cost control, flexible delivery times and above all, tighter stock control. Stock control is particularly important because of the large amounts of working capital involved.

Therefore, modern grocery retailing is characterised by sophisticated and well managed operations where progressive economies of scale make it difficult for manufacturers to increase their market power. The degree of concentration is now such that for a manufacturer's brand to be financially successful, it has to be stocked by the main multiples. Furthermore, concentration is likely to continue until the Monopolies and Mergers Commission restricts the growth of any individual chain. A 1985 ruling concluded that retail practices were not unfair because their actions were limited by internal competition and there were no signs that it was against the public interest.

It is within such an operating environment that we examine private labels. We now consider the reasons which are often given by researchers and retailers alike in using private labels.

1.2b Why Retailers Use Private Labels

The overriding pressure on retailers today is to compete effectively and efficiently in order to generate sufficient funds to develop and sustain a competitive advantage. Retailers use a mixture of strategic tools to achieve this, including private labels. Private labels play a central role by providing

retailers with a means of differentiation, higher profit margins and more operational control.

Private labels are said to be used for the following reasons:

- * To provide the retailer with a means of differentiating their offerings from those of other retailers and so build a competitive advantage (Frank and Boyd 1965, Leahy 1987).
- * To build and sustain customer loyalty to the store (Simmons and Meredith 1984, Dunn and Wrigley 1984, Cunningham 1961, Retail Business 1971, Leahy 1987).
- * To provide the retailer with profit margins around 5% higher than from manufacturer's brands (McGoldrick 1984, Euromonitor 1986).
- * To gain loyalty throughout the store by capitalising on the familiar 'umbrella name' as customers are prone to buying the store's private label in many product fields (Rao 1969a).
- * To introduce new products and/or extend existing ranges (Leahy 1987).
- * To make a quality statement about the store (McGoldrick 1984).
- * To provide the retailer with more operational control through product rationalisation, as costly slow-moving brands are replaced with high volume private labels; shelf space can be more profitably allocated; even price control is obtained to some degree as private labels can be strategically priced to ensure certain differentials are maintained (Myers 1967, Stern 1966).
- * To provide 'good value for money' to their customers (Leahy 1987, Bond 1984, Martell 1986).

There are two main interrelated themes here - differentiation and operational efficiency, both of which are intended to translate into market share and feed through into improved profits for the retailer. Though the thesis is more concerned with the former theme, it by no means minimises the importance of

the latter. For retailers to gain a competitive advantage from offering private labels in the ways detailed above (eg. more loyalty to "their" private label), requires that their customers buy each store's private label selectively, and that this differs from the way in which brands are bought.

There is something of a paradox if private labels are used as a differentiating tool. As one retailer tries to differentiate itself, others react in a defensive manner. Such tactics tend to be short term as they are easily and quickly copied. The majority of retailers now offer a private label with KwikSave being the only sizeable grocery retailer still pursuing a brand-only policy. Therefore, unless the consumer perceives each store's private label to be different; and more importantly this is reflected in her purchasing, the use of private labels as a successful differentiating tactic is questionable.

However, even if retailers do not gain a competitive advantage from offering private labels, this does not mean they are unsuccessful. Indeed, if they can attract the same purchasing as brands, and at the same time provide greater operational control, the retailer will still gain financially over a brand-only policy. Private labels do not, for example, have to attract greater loyalty from their buyers in order to justify their existence.

Despite these points, it is widely believed that retailers are the main benefactors from private labels (Euromonitor 1986, Simmons and Meredith 1984). For manufacturers too, there can be advantages in supplying private labels. These include off-loading excess capacity, lowering their distribution costs and avoiding the expense of national advertising campaigns. But by the same token, they take the risk of undermining their branded goods and becoming over-reliant on a few buyers (Morris 1979). Customers also benefit from having value for money with a minimal sacrifice in their range of choice. On average private labels have been shown to be 15% cheaper than brand leaders (Euromonitor 1986).

The thesis is primarily concerned with establishing empirical regularities for the buying patterns of private labels. This then enables us to compare brands and private labels, and interpret any differences accordingly. Only when we know how people buy private labels and whether this differs from how they buy brands, can we determine whether retailers strategic use of them is justified in the manner outlined above.

We now outline buyer behaviour theory and the analysis techniques used in this study of private labels.

1.3 BUYER BEHAVIOUR

The thesis draws heavily on the empirically-based theory of buyer behaviour (Ehrenberg 1972, 1988). It is a descriptive theory which focusses on buying behaviour only as it is reflected in actual purchase behaviour.

Intuitively we believe that individual buyer behaviour is complex, even for low involvement decisions. There are pre-purchase needs and attitudes, the experience of previous usage, and external influences such as advertising, promotion and retail availability. Each time a shopping trip is undertaken, various choices are available and decisions have to be made about:

- which store to visit
- whether to buy the product
- which brand or private label to buy
- which pack-size or flavour to buy
- how much to buy

This complexity is further compounded by the fact that there are many buyers in the marketplace, with different needs, values, attitudes and consumption rates. Moreover the marketing environment also exerts varying degrees of influence on the behaviour of these individual buyers. So there are many different buying situations and an almost bewildering set of choices and decisions to be made by the buyer.

Yet despite such complexities, simple regularities have been observed at the aggregate level in the purchase of frequently bought consumer brands. Early work on fast moving consumer goods appeared in articles by Ehrenberg (1959, 1969) and Ehrenberg and Goodhardt (1970). This and other work was brought together in Repeat Buying : Theory and Applications (Ehrenberg 1972, 1988). This research questions many of the conventional wisdoms of marketing and raises questions on some of the traditional ideas about brand loyalty, brand image, segmentation, and the effects of advertising. These issues are discussed in chapter 9.

In as far as the individual consumer is dealing with frequently bought, low priced items, the amount of risk involved is low. When differences between items are

small, there is ample opportunity to develop habits to simplify the repetitive choice situation. It may be equally rational to buy the same brand as before, or to switch to another on this purchase occasion. Empirically the finding is that most people tend to develop the habit of buying one or some small number of brands fairly regularly (Brown 1952 and 1953, Ehrenberg 1959).

Such regularities found in buying behaviour mean that at the aggregate level, patterns are observed "as if" behaviour is regular. It is such uniformity at the aggregate level that provides the analytical framework within which these analyses are conducted.

What the reasons are for such simplifying tendencies to exist in respect of buying are not the main issue of this thesis, though some conjectures are drawn in chapter 9. First one needs to know what people do, before going on to try and explain why. Further, such findings need to be generalised over different environments and situations to ensure some robustness before any theory which describes and interrelates these findings is proposed.

We now consider the data used before going on to outline the objectives of the study.

1.3a Data Used

The main data analysed are records of what households buy, week by week. These records are obtained from consumer panels which are market research operations where purchases in a specific product class are continuously measured for a sample of informants within each ITV region.

The consumer panel data used in the thesis is operated by Audits of Great Britain (AGB) Ltd. Weekly purchases are collected by means of an in-home audit which are then reported four weekly. An in-home audit is where an interviewer records purchases of groceries in the panelist's home, rather than an uncontrolled diary audit where the panelist completes a diary recording her own purchases (see Appendix 1 for example diary). Diary panel data have been shown to be a reliable source of data for such longitudinal studies as are undertaken in this thesis (Sudman 1964a, Sudman 1964b, Sudman and Ferber 1979).

AGB use an in-home audit because this allows for the collection of more

detailed data by trained interviewers rather than relying on individual consumers. When details such as size, fragrance etc are required, a self completion diary is likely to be more prone to error. However, as with any sort of data collection procedure, there are some problems with panel data and these are discussed in chapter 8.

Three forms of data are used:

1. Market Analysis Packages for the 5 product fields detailed below (Table 1.1) where the data are provided in a tabulated format. In addition to buyer behaviour statistics, there are demographic details which include: age of housewife, social class, presence of children, household size, housewife working status and ITV watching frequency.
2. Raw data for Fruit Squash and Liquid Fabric Conditioner product fields for 48 weeks in 1985. The more detailed analyses are undertaken on these two product fields.
3. Supplementary sources included information on the UK biscuit market; Automatic Washing Powder, Tea Bags and US Ground Coffee market. The latter is from diary panel data from the Market Research Corporation Of America (MRCA).

Table 1.1 : Summary of Panel Data Used in the Study

Product	Region	CR	Year	B%	W
Raw Data (48 weeks)*					
Fruit Squash	London	650	1985	72	10.5
	Lancashire	650	"	78	13.8
Liquid Fabric Conditioner	London	650	"	60	6.7
	Lancashire	650	"	63	6.8
Market Analysis Package (52 weeks)					
Baked Beans	London	673	1984	93	31.5
	Lancashire	777	"	95	34.7
Instant Coffee	London	673	"	90	12.3
	Lancashire	777	"	92	14.2
Washing Up Liquid	London	673	"	97	9.5
	Lancashire	777	"	96	11.9
Average		695		84	15.2

- Key :** CR = Continuous Reporters (ie those who remain on the panel throughout the 48/52 week period which is essentially the sample size)
- B% = Penetration (ie. proportion of the sample purchasing the product field)
- W = Average Purchase Frequency (ie. how often they buy the product field in a given time period)
- * = Market Analysis Packages were also provided for these two product fields.

AGB undertook some panel changes between 1984 and 1985 which accounts for the changes between regional panel sizes during the two years. However, these were boundary changes only. Following the revision of ITV area boundaries in 1983, a number of improvements were made to the reporting service and these were introduced from January 1985. Prior to this there was some overlap between ITV regions so that the sum of these parts was greater than for the whole country. This arose because some households on the boundary had access to more than one ITV station and were consequently double counted.

To overcome this problem the boundaries were redefined in such a way that the sum of the households in each region was equivalent to the total number of households in the UK. This has in no substantive way affected the resulting data as the sampling technique and data collection procedures remain the same. AGB have conducted their own tests in-house to compare data before and after these changes.

Raw Data

Each purchase record contains the following information: the household identity code; the product and brand bought; the store chain from which it was bought; the quantity purchased; the actual price paid; whether it was a brand or private label; the week in which the purchase was made, and whether it was a large, medium or small pack-size.

Panel members include those who reported continuously throughout the 48 week period, irrespective of whether they purchased any of the product field or not. On the AGB panel, approximately 80% of those at the start of the year report continuously throughout. There is therefore an attrition rate of 20% due to people leaving. They are replaced so that the panel remains representative of the region. The number of buying households refers to those who made at least one purchase during the period.

Items were selected for analysis on the basis of their market share. For Fruit Squash and Liquid Fabric Conditioner there are 8 itemised brands and private labels for each product field respectively. Each product field has a further two categories for other brands (OB) and other private labels (OBPL). These two groups are necessary to take into consideration all those purchases not itemised elsewhere (Appendix 2).

Items with small sample sizes (20 households or below) have been aggregated into the OB and OBPL categories. This is because their results are often deviant, being greatly influenced by a small number of individuals.

For the within-store analyses, we examine four store chains in detail; Sainsbury and KwikSave in Lancashire, and Tesco and Sainsbury in London. These account for over half the grocery sales in each region. The remaining multiple retailers and the majority of smaller supermarkets and independents have been grouped into a miscellaneous category (Appendix 3).

Other Product Fields

Baked Beans, Instant Coffee and Washing Up Liquid are used to test the extent to which findings generalise. Their fixed tabulated format means analyses are limited to those available in the Market Analysis Package. Unfortunately no store level information is available in the package for these product fields.

1.3b Reasons For This Data Selection

Private label market shares vary greatly nationwide. This is mainly the result of differences in retail distribution, private label policy and product field variations. Such differences make the study of private labels informative because we can make extensive comparisons across differing retail situations. It also means that we can see if results can be generalised across different environments which enhances their robustness.

Though there is a trend towards more national distribution, especially amongst the multiples, regional variation in market shares still exists. The share of all grocery trade within each region which is held in total by the main multiples is similar; in London they have some 70% of the packaged grocery trade, whereas in Scotland their share falls to around 60%. The independents share of trade is approximately 10% nationwide. However, individual retailers differ in their attitudes towards private labels, from those offering an extensive range to those who have none.

London and Lancashire were selected for three main reasons. First, because private labels are strong in London and weak in Lancashire, a reflection of the dominance of different retailers in each region. This means we have a range of private label market shares over which to make comparisons. Secondly, because retail distribution differences are maximised with Sainsbury's London dominance and relative obscurity in Lancashire and vice-versa for Asda and KwikSave. This enables us to compare buying in stores with quite different private label policies. Finally, because AGB panel sizes are largest in these three regions, and this goes some way to overcoming the problems of small sample sizes.

Private label penetration also varies by product field. In confectionery for example, they are practically non-existent whereas they have 75% of the flour market. The five product fields were selected so that a wide range of private label market shares were reflected, from 15% to over 50% (Table 1.2).

Table 1.2 : Variation in Private Label Market Shares

Product	Region	Private Label Market Share %
Fruit	London	56
Squash	Lancashire	20
Fabric	London	37
Conditioner	Lancashire	20
Baked	London	54
Beans	Lancashire	15
Instant	London	36
Coffee	Lancashire	24
Washing Up	London	29
Liquid	Lancashire	16
Average		31

1.3c Objectives Of This Study

There is a gap in the study of private label purchase behaviour. This study attempts to bridge the gap and to explore and establish regularities in the area of private label purchase behaviour. There are four objectives listed in order of their importance:

1. To determine how people buy private labels.

This is achieved by establishing and exploring regularities in private label purchase behaviour. We examine buying patterns in five product fields and compare observed values with theoretical predictions from the Dirichlet and Negative Binomial (NBD) models. This knowledge can then be used to focus on more applied issues.

2 To identify any differences and similarities in how people buy brands and private labels.

This is achieved by comparing brand and private label purchase behaviour with each other and against the model predictions. Consistent differences and similarities are sought and these are examined further to determine whether they are due to statistical effects or whether they reflect real

differences in private label buying behaviour. This is then used as a basis for discussing retail strategy issues.

3. **To determine whether private labels provide the retailer with a competitive edge in respect of how people buy them.**

Retailers use private labels as a means of differentiating themselves from the competition in such a way that they achieve a competitive advantage. We examine how private labels are bought within store chains, within product fields and across two product fields to determine whether people buy them in such a way as to provide the retailer with any competitive advantage.

4. **To determine whether there is there any evidence of private label proneness.**

We examine whether people who buy private labels in one product field are more or less likely to buy them in another, and whether this applies to private labels generally (general private label proneness) or to those of specific stores (specific private label proneness). This is achieved by comparing how the same people buy brands and private labels across two product fields.

As a consequence of these objectives, we will also test and extend the generalisability of the NBD and Dirichlet models in predicting private label purchase behaviour and identify any new empirical results not hitherto found in studies of brand and store choice.

It must be stressed that this study does not aim to provide a full explanation for any regularities that are shown to exist.

- " it is not the function of an empirical generalisation to suggest its own explanation. Such generalisations must stand....until someone provides an explanation for them."
 (James Coleman 1962)

Some attempt at explaining why these patterns of buying behaviour occur is made by interpreting results, but a full explanation is left for further work. However, a stochastic theory gives important insights; for example, in this study it successfully describes how people buy, which when coupled with our model assumptions (as we shall see later) enables us to suggest reasons for why behaviour is as described.

1.4 THESIS STRUCTURE

The fundamental issue examined is whether private labels are bought in the same way as brands, and whether this is as predicted from theory. In light of these findings, what interpretations can we make in respect of their use in retail strategy?

There are 3 parts to the thesis, which consists of nine chapters.

Part 1 - Chapters 2 and 3 - Methodology

In Chapter 2 we discuss the research design and examine the nature of the NBD and Dirichlet models and explain why they, in particular, are used in the thesis. In Chapter 3 we describe buyer behaviour and the analysis framework used. Then we elaborate on the two stochastic models used and show worked examples of each.

Part 2 - Chapters 4, 5, 6 and 7 - Results.

In line with the research objectives outlined in section 1.3c (page 32), the analysis is conducted in 4 stages.

In chapter 4 we examine whether private label purchasing exhibits any empirical regularities, as have been found to exist in brand purchase studies. Brand and private label purchasing are compared with each other and with the theory.

In chapter 5, having established such regularities, we focus on the main consistent difference which exists between brand and private label buying behaviour. Various explanations are provided and these are examined in turn. These relate to methodological issues, model assumptions, and "real" differences in how people buy brands and private labels. The methodological implications of such findings are considered, with particular emphasis on how the limited distribution of private labels needs to be accounted for in any comparison with branded goods.

In chapter 6, private label purchasing within store chains is examined. Due consideration is given to the methodological issues raised above. Other more minor differences between brand and private label purchasing which were not addressed in chapter 5 are examined here. We investigate whether each store's private label is bought in the same way; whether purchasing within store chains differs from that in the market place generally; whether buying patterns in stores with private labels are the same as those in KwikSave, where no private labels are offered.

Finally, in chapter 7 we examine purchasing across two product fields. Here we ask whether those people who buy private labels in one product field, are more or less likely to also buy them in another. Private label proneness is often assumed to occur and using this method of analysis we can see whether there is any empirical evidence to support this.

Part Three - Chapters 8 and 9 - Discussion

In chapter 8 we discuss the limitations of this study and pinpoint areas for future work. Then in the final chapter 9, findings from the thesis are drawn together and discussed in more detail. Here we focus on the practical and theoretical implications of the research with the retailer very much in mind.

CHAPTER 2 : THE THEORETICAL MODELS

2.1 Introduction

2.2 Research Design

2.2a Panel Data

2.2b A Model-Based Approach

2.3 Reasons For Using Stochastic Models Of Buyer Behaviour

2.3a They Are Empirical

2.3b They Are Descriptive

2.3c They Are Particularly Suited To Panel Data

2.3d An Extensive Body Of Research Exists

2.4 Reasons For Using NBD And Dirichlet Models

2.4a They are Successful

2.4b They Are Valid And Reliable Research Tools

2.4c They Are "Good" Models

2.4d They Satisfy Our Research Objectives

2.1 INTRODUCTION

The main purpose of this chapter is to explain the reasons for adopting the chosen research design. That is, the use of two stochastic models of buyer behaviour, the Negative Binomial Distribution (NBD) and Dirichlet models, and the application of these to panel data.

This chapter is divided into 4 sections. In section 2.2, we discuss why panel data and a model-based approach are used. Then in section 2.3, we explain why stochastic models are appropriate for this research application. Finally, in section 2.4 reasons for using the NBD and Dirichlet model in particular are given. The justification is in terms of satisfying the research objectives and research methodology standards more generally.

2.2 RESEARCH DESIGN

The thesis objectives are largely empirical in nature, with theoretical development being of secondary importance. This being so, the research design is chosen accordingly; panel data are analysed with two stochastic models of buyer behaviour.

2.2a Panel Data

The main objective is to examine how people buy private labels and compare purchasing patterns with those for brands, and with the model predictions. Various questions are asked such as: How do people buy private labels in terms of the number of people buying and the rate at which they buy. Does this differ for each store's private label? Do people buy brands and private labels interchangeably? In order to answer such questions, we require data on peoples' actual purchasing patterns in a variety of product fields over time.

Data which enables us to answer such questions could have been obtained by visiting various multiple retailers and conducting a survey, or by using secondary data of the required format.

Secondary data were used. It would have been operationally impractical to collect the necessary data first hand. Information from shoppers leaving the store would only provide a snapshot of purchase behaviour at that point in time and relying on memory recall for past purchases would be liable to much error. Detailed information on how people switch between brands and private labels over many shopping trips would also not be forthcoming. Therefore,

unless the same buyers could be persuaded to be part of a continuous survey (which would be costly and time consuming), this method is inappropriate given the research objectives in hand.

So panel data was chosen because it was appropriate given the sorts of analyses to be undertaken in the thesis. Panel data is where the purchase behaviour of a sample of consumers is observed over a continuous time period. For example, purchasing is examined by product field, brand, region and consumer type as well as for different length time periods. There is also the facility to dip into other product fields as and when required which is important to see if results can be generalised. Also, panel data has been used to measure brand buying behaviour in the past so has a proven track record in this type of research. Furthermore, AGB generously made the data freely available for research purposes.

2.2b A Model-Based Approach

A model-based approach was selected because it satisfies the research objectives.

Given the emphasis on comparative measures of buying, it was important to establish an interpretive norm against which to make such comparisons. A model provides such a norm. For example, if in a given time period, 60% of the population buy private label X, is this high, low or just about right? The figure needs to be set in context so as to be interpreted in this manner.

In addition, models can help to structure large amounts of data so that extensive comparisons are easier to handle. Also, they are readily applied to many data sets which is important in order to generalise results.

There are also other research requirements which need to be considered. But these are more relevant to choosing the specific model as is discussed below.

2.3 REASONS FOR USING STOCHASTIC MODELS OF BUYER BEHAVIOUR

One of the fundamental questions asked about consumer behaviour is whether it is at least partially stochastic, or whether there exists causes and explanations for such behaviour. In line with these two differing views, there are a variety of approaches to modelling consumer purchase behaviour. Each approach has its own strengths and weaknesses and is appropriate for a given situation.

The deterministic view proposes that purchase behaviour is a direct consequence of certain causes which affect the consumers underlying behaviour. Various models are used to help understand the influences on an individuals purchase behaviour. For example, behavioural models, such as the Howard-Sheth model (Howard and Sheth 1969) shows the buying process conceptually in terms of explanatory variables (for reviews see Engel et al (1986), Ehrenberg and Pyatt (1971), Kotler (1967 chapter 4); regression models try to explain the impact of such as price, quality, promotional activity etc on purchase behaviour; and attitude models where the cognitive school of thought proposes that attitudes can be used to predict the intention of individuals to behave (Fishbein 1963, Fishbein and Ajzen 1975).

The stochastic theory proposes that many so many variables affect consumer behaviour with unpredictable frequency, that it can be described as if it were random. Stochastic models are used in the thesis.

Stochastic models are defined as "models in which the probability components are built in at the outset rather than being added ex-post-facto to accommodate discrepancies between predicted and actual results. That is, the probabilistic components form an integral part of the basic structure of the stochastic model" (Massy et al 1970). However, stochastic models do not mean that consumers make their purchase decisions by flipping coins, rather that individuals each have different reasons for purchasing brands which when aggregated are sufficiently irregular to be summarised as if they were stochastic. As Bass (1974 page 2) asserts: even if behaviour is caused but the bulk of the explanation lies in a multitude of variables which occur with unpredictable frequency, then, in practice, the process is stochastic. It is therefore a "structured" kind of randomness.

The primary function of stochastic models is to provide both description and prediction of buying behaviour at the aggregate level. For example, the NBD describes how people buy individual brands in a product field. Being able to describe these patterns of buying behaviour successfully means the model can also be used to predict what would happen under certain conditions as well as providing a framework for analysis.

Sometimes, they can also help to provide an understanding of the structure of the underlying buying process. For example, the NBD assumes that individual purchases follow a poisson distribution and that different individuals have long-run average buying rates distributed according to a Gamma distribution. So this does go some

way towards understanding the underlying structure which is then helpful in interpreting results.

Stochastic models are used in the thesis because they satisfy our research objectives:

2.3a They Are Empirical

Stochastic models enable us to examine panel data and determine how people buy private labels over time.

Conceptual models cannot be used directly because they do not enable us to study and report systematic patterns of actual private label purchase behaviour. For example, the Howard and Sheth model is a classic conceptual model with little evidence to show how it relates to fact. Attempts to test it have failed to explain much of the variance in consumer behaviour (Farley and Ring 1970). This is largely because of the difficulty in defining terms operationally, which is a common problem with such models.

Attitude models are also inappropriate because we need to determine how people behave and learn something systematic and general about private labels. Attitude models concentrate on reported behaviour or intention to behave rather than actual behaviour.

2.3b They Are Descriptive

The thesis emphasis is on how private labels are bought rather than directly why they are bought. Stochastic models enable us to describe private label buying patterns which is necessary before going on to examine why this is so.

Attitude, behavioural and regression type models are better suited to exploring the decision making process and in trying to identify those characteristics which are influential. They are therefore more concerned with why people buy and understanding the decision making process. They may be useful in explaining any empirical findings which originate from these analyses, but this will be left largely for further study.

Indeed research is already underway to examine why private labels are bought. For example, how situational factors such as "for parties" and "for private use" affect private label purchasing (Klollaris 1990). Others (Chernatony 1988,

Chernatony 1987), have examined attitudes towards private labels and found that people appreciate that brands and private labels offer similar quality, whereas generic items are perceived to offer lower quality.

2.3c They Are Particularly Suited To Panel Data

Stochastic models were originally developed to examine panel data. Conceptual and attitude models require different forms of data which would not provide empirical information on peoples' buying patterns over time as we require for this study. Though attitude panels exist, they relate to why people behave as they do, rather than how, as we need in the first instance. Regression models can be applied to panel data but they too focus on explaining buying behaviour.

2.3d An Extensive Body Of Research Exists

Given the comparative nature of the study, it is important to have a well-established body of research against which to compare private label buying behaviour.

Much successful work has been undertaken on consumer purchasing patterns using stochastic models (Ehrenberg 1972, 1988). Consequently there is a well established empirical and theoretical body of knowledge which can be used as a reference point. There is no such empirical body of knowledge for behavioural models because attempts to relate them to fact have rarely led to systematic and generalisable findings. Attitude models have generated some empirical results, but have not had the same success as stochastic models in brand choice applications (Bass et al 1975). For example, much of the successful work here has been for high-involvement situations such as attitudes towards ethnic minorities. In fast moving consumer goods studies it has been found that usage, rather than attitude, is more likely to predict intention to buy (Bird and Ehrenberg 1966, Barnard et al 1986).

Though many stochastic models have been applied to consumer purchasing, only a few can realistically be used for the study of private label purchase behaviour. The NBD which is a purchase incidence model, and the Dirichlet which is a brand choice and purchase incidence model are used in the thesis. These are discussed in detail in chapter 3 and we now explain why this choice was made.

2.4 REASONS FOR USING THE NBD AND DIRICHLET MODELS

There are many stochastic models of consumer behaviour (see appendix 3 for an outline of some of these models, and Massy et al (1970) for more details). However, only two, the Negative Binomial Distribution (NBD) and the Dirichlet model are used in the thesis. The NBD is a purchase incidence model which shows how a chosen brand is bought; the Dirichlet, a brand choice and purchase incidence model which provides predictions for all items in the product field rather than one item at a time. The Dirichlet specifies how many purchases of the product class are made in a given time period and with what probability a consumer chooses a brand from those available. (More details of these models are given in the following chapter.)

These two models in particular were selected because:

2.4a They Are Successful

Of the many stochastic models used to reflect consumer purchase behaviour, the NBD and Dirichlet are the most successful (Morrison and Schmittlein 1988). The NBD was originally applied to buyer behaviour in 1959 (Ehrenberg 1959) and findings have since been widely generalised. The Dirichlet which is an extension of the NBD, has only recently been applied to buyer behaviour (Goodhardt, Ehrenberg and Chatfield 1984, Kau and Ehrenberg 1984, Ellis and Uncles 1989 Appendix 12, Uncles and Ellis 1989a Appendix 10, Uncles and Ellis 1989b Appendix 11) and results from these analyses have also been successful. Therefore, though the NBD has been more extensively tested than the Dirichlet, both have been shown to work well in practice.

This is important in our study because we need to compare private label buying behaviour against some well established body of research so as to assess whether or not they are bought like brands and to provide scope for interpreting any differences that may exist.

Other stochastic models of buyer behaviour have only been tested on a limited basis. The NBD and Dirichlet have been shown to work for many product fields, different length time periods, for different countries and regions, for food and non-food products, and for industrial buying and store choice decisions (Ehrenberg 1975, Kau and Ehrenberg 1984, Easton 1976, Stern 1990, Ehrenberg and Goodhardt 1969).

Researchers have attempted to improve on the NBD's performance by looking

for new ways to model buyer behaviour. Such attempts involve either new applications of existing models, or simply extensions of those already in existence. However, even here, those variations which work well use the NBD distribution somewhere in the specification (Morrison and Schmittlein 1988, Jeuland et al 1980, Zufryden 1987, Bass et al 1975).

2.4b They Are Valid And Reliable Research Tools

Validity refers to the degree to which an instrument truly measures the constructs it is intended to measure. Reliability refers to the degree to which the measure is free from variable error. So a perfectly reliable model would yield the same results on different occasions.

Since its original application to buyer behaviour (Ehrenberg 1959), the NBD has been extensively generalised. It has been found to work well in many different situations and has been shown to be robust. Small improvements have been achieved, but not without adding to the models complexity. For example, an Erlang-2 distribution was substituted for the Poisson (Chatfield and Goodhardt 1973). However, the results were not sufficiently improved to warrant the added complexity. The Dirichlet, which is an extension of the NBD, though not as well tested, is now becoming more widely used. The Dirichlet has also been shown to work well in numerous applications (Ellis and Uncles 1989, Uncles and Ellis 1989a, Uncles and Ellis 1989b, Lamb and Goodhardt 1988, Goodhardt, Ehrenberg and Chatfield 1984).

Extensive tests by different researchers have also helped to establish the NBD model's credibility as a valid and reliable research tool (Morrison and Schmittlein 1988). This is especially important here because marketers have often been criticised for not paying enough attention to basic measurement issues (Jacoby 1978).

Given the empirical emphasis in this thesis, external and predictive validity are important. Findings need to be generalised to the wider buying population for them to be of any use to practitioners. Furthermore, the research hinges on the model being a reliable measurement tool against which comparisons are made.

2.4c They Are "Good" Models

Little (1970) suggested a good model should be simple to use, robust, easy to

manipulate, adaptive, complete and relatively easy to communicate and understand. The NBD and Dirichlet are both therefore good models.

They both require simple parameter estimation. The NBD requires only 2 inputs per brand; the average purchase frequency and penetration in the base period. The Dirichlet requires these, plus the same for the product field as a whole. Furthermore these values are readily available from panel data.

Both models have been shown to be robust in many differing situations. There are cases where consistent deviations have been noticed, but the models have not broken down, rather this has helped to identify interesting differences between the items under study (Ehrenberg 1988).

Both models are relatively easy to manipulate. However the software used is not specifically designed for this purpose. So in some places, analyses may appear cumbersome. The models can be easily transported to other data sets. This is particularly important in these analyses where extensive generalisations are made.

Results on buying patterns are easy to communicate. However, understanding the inter-relationships between these results tends to be more complex and therefore more difficult to convey. An attempt is made, in chapter 3, to produce a conceptual framework to clarify the inter-relationships.

2.4d They Satisfy Our Research Objectives

Both are empirical, provide results on how private labels are bought, are suited to panel data, and have resulted in a well developed empirically derived theory of buyer behaviour which provides us with a strong framework for analysis.

Furthermore, the Dirichlet allows considerable scope for examining peoples' brand and private label repertoires which is important given retailers objectives in using private labels. Issues such as private label proneness and loyalty can be considered with respect to product field purchasing, purchasing across two product fields and within store chains. Private label results can then be set against what is already known about peoples' brand purchase repertoires.

Therefore, the choice of research methodology is based on satisfying our research

objectives in such a manner that the emphasis is on examining how private labels are bought, rather than on testing out relatively untried models. Though other stochastic models also satisfy our research objectives to some extent, they have not been sufficiently well tried to provide a reliable basis for comparison. We now discuss the NBD and Dirichlet models in more detail.

CHAPTER 3 : THE NBD AND DIRICHLET MODELS

3.1 Introduction**3.2 Buyer Behaviour Theory****3.2a Development Of Buyer Behaviour Theory****3.3 The Analysis Structure****3.3a The Multiplicative Sales Equation****3.3b Theoretical Comparisons****3.4 The Negative Binomial Distribution (NBD)****3.4a The Theory****3.4b The Mathematics****3.4c Fitting The NBD****3.4d An Example - Repeat Buying Of A Brand****3.5 The Dirichlet Model****3.5a The Theory****3.5b The Mathematics****3.5c Fitting The Dirichlet****3.5d An Example****3.6 Stationarity and Market Segmentation****3.6a Stationarity****3.6b Market Segmentation****3.7 Summary**

3.1 INTRODUCTION

The purposes of this chapter are twofold; to introduce buyer behaviour theory and discuss the main issues; then to introduce the analysis framework adopted and models used in the thesis.

This chapter comprises 4 main sections. In section 3.2, we examine the theory of buyer behaviour, its development, and outline some of the main regularities found. In section 3.3, we outline the analysis structure adopted in this and all further empirical chapters. Finally, in sections 3.4 and 3.5, we examine the NBD and Dirichlet models; we discuss their assumptions, the mathematics, how the models relate to actual purchase behaviour, and show a worked example of each.

3.2 BUYER BEHAVIOUR THEORY

For many years, consumer behaviour has been characterised by two research approaches which have rarely come together. These are conceptual models and ad-hoc empirical studies.

On the one hand there are conceptual models such as that proposed by Howard & Sheth (1969). Though the conceptualisation of the decision making process intuitively appears to resemble reality, there is no evidence of how this relates to fact. Indeed this may not be the intention. Perhaps they are, at this stage, just ways of conceptualising consumer behaviour. When more sophisticated data is available which permits their testing, this may change.

At the same time there is much information from ad-hoc problem orientated surveys and other forms of research such as retail audits. Market research companies, for example are constantly undertaking surveys on behalf of different clients. However results are rarely released for reasons of client confidentiality; nor are they combined in an attempt to develop a more extensive body of research in the area. Academic models and theories have seldom been applied to these studies so there is little integration between the two research methods.

This lack of systematic integration has hindered the development of marketing theory. Models without facts remain conceptualisations of the system of interest. They could be used diagnostically and for predictive purposes if only their validity was tested. Similarly empirical results in isolation, cannot contribute to an understanding of the underlying features and interrelationships of the system

without being pulled together with some theoretical basis.

The empirically derived theory of buyer behaviour, which we refer to in our analyses, is one of the few attempts in consumer behaviour to integrate the two in a continuous and systematic manner. A concerted effort has been made to build, develop, improve and test the models so that a body of research emerges which is both supported by fact and makes sense intuitively. This process was helped by the availability of panel data which provided a rich source of continuous buying behaviour which could be used to test these models under many different conditions.

We now outline the development of this theory and some of the main regularities found, before going on to explain how the models relate to buying behaviour.

3.2a Development Of Buyer Behaviour Theory

Sir Cyril Hinshelwood (1957) suggested there are three stages through which scientific theory passes:

- * The first is usually a gross over-simplification resulting partly from the need for practical views and even more from a too enthusiastic aspiration for the elegance of form.
- * The symmetry of this hypothetical system is then distorted and neatness marred as facts increasingly rebel against uniformity.
- * If and when this stage is reached, a new order emerges, more intricately contrived, less obvious and its parts more subtly interwoven.

This describes the development of buyer behaviour theory. The initial development was characterised by a series of disjointed underlying patterns in the data. However, further work revealed that though the average purchase rate varied, it did so in a systematic manner across the product field and this finding subsequently became the lynch-pin for other findings. Isolated findings of this nature were pooled to develop a more comprehensive picture of buying behaviour. Though this approach is rather unorthodox in the social sciences, it has produced a successful and robust theory of consumer behaviour.

There are now a series of empirical regularities, some of which are described

below, which can be closely predicted by the NBD and Dirichlet models. They provide the framework within which we conduct our analyses. Some examples of these buying regularities include:

- * In the buying of a product or brand, the frequency distribution of purchases generally follows a positively skewed downward sloping curve. This can be approximated by the NBD (which is also used in the Dirichlet model). We find this pattern occurs irrespective of whether one is buying an individual item or group of items. This means that of those who buy, most do so infrequently, relatively few buy heavily.
- * Another form of regularity is that the average purchase frequency of different items in a product field varies little within a given time period. Differences in market share are marked mainly by differences in penetration which is more variable between items in the product field. Therefore, big items have a higher market share mainly because they have a higher penetration than others in the product field.
- * The average purchase frequency and penetration in a product field are related by a law called Double Jeopardy; that less popular brands are bought by fewer people, and those who buy them do so less often.
- * Repeat buying is also predictable from the penetration and average purchase frequency. Repeat buying depends mainly on purchase frequency because this is like an index of the disposition to buy. The more strongly disposed are buyers, the more likely they are to buy the next time round. Repeat purchasers buy at a somewhat higher rate than do all buyers, whilst new buyers buy at a fairly constant rate.
- * Most buyers in longer time periods are multi-item buyers ie they do not confine their purchases to one particular item but have a repertoire from which to choose. The extent of this duplicate buying is dependent on the number who buy the item at all. So of item X buyers, some will also buy item Y. Larger items tend to attract more duplicate buyers than do smaller ones.

These regularities are now well established (Ehrenberg 1988). They have been

widely generalised and as such provide a sound framework in which to examine private label purchase behaviour.

These regularities coupled with the model assumptions can be interpreted in terms of market segmentation, competition and loyalty. However such issues are left for discussion in sections 3.4 and 3.5 and are covered in more detail in chapter 9. First we examine the analysis structure used in the thesis.

3.3 THE ANALYSIS STRUCTURE

A standard framework is used which hinges around the two summary measures, penetration and purchase frequency. Together they make up the sales equation which we describe below. These summary measures and others are compared with theoretical predictions in order to identify differences and similarities between brand and private label purchase behaviour.

3.3a The Multiplicative Sales Equation

$$\text{Sales} = N * b * w * q$$

where N = number of households in the population

b = percent of population buying the brand in a given period

w = average purchase frequency in the same period

q = quantity bought per purchase

Of these 4 variables, the size of the population (N) is more or less predetermined in the short run. With the exception of some products (such as cigarettes), most people only buy one unit, on each purchase occasion. Therefore, the quantity bought (q) can also be considered as fixed. The remaining 2 variables, b and w are of greater importance in determining sales in the relatively short run (ie less than one year).

Therefore, for our purposes: $\text{Sales} = \text{approximately } b * w$

These two measures of buyer behaviour are used to summarise the data within each of the following three analysis sections.

First, we examine buying individual brands and private labels over time periods of different lengths. For each brand and private label, the penetration (b) and

average purchase frequency (w) are calculated, and these are compared with the Dirichlet predictions. This is our components of the sales equation analysis section.

Then we examine how people buy from one time period to the next. For example, taking two periods of equal length, there will be repeat buyers who buy in both periods; new buyers who buy just in the second; and lapsed buyers who buy in the first period only. We calculate b and w for each sub-group and compare these with NBD model predictions. This provides a detailed picture of what is happening to sales over time. This is essentially the **period to period buying analysis**.

Finally, the focus changes to how people buy across the product field. Some buyers may only purchase one particular item in a given time period, whereas others have a more diverse repertoire. b and w are calculated for sole (100% loyal) buyers and those with a repertoire. We also examine how buyers spread their purchases across the product field. This is essentially the **product field buying analysis**.

The three analysis sections combine to provide us with a means of examining the components of sales, how these vary with lengths of analysis period and how they relate to product field purchasing. This is shown schematically (Table 3.1). So peoples' buying patterns can be examined over time and in terms of differences in their loyalty to particular items.

Table 3.1 : Buying Components

Components Of The Sales Equation b w	
Period To Period Buying b w repeat, new and lapsed buyers	Product Field Buying b w sole, multi and product field buyers

Observed measures are calculated in line with the analysis structure outlined above. Results are then compared with theoretical estimates provided by one of the two stochastic models. The Dirichlet is used predominantly, with the NBD for repeat buying and purchase frequency distribution predictions (Table 3.2). (The terminology is defined in more detail in chapter 4.)

Table 3.2 : Buyer Behaviour Measures Generated From Each Model

N B D		DIRICHLET	
repeat buying	br	penetration	b
repeat rate	wr	average purchase frequency	w
new buying	bn	product field buying	B
new rate	wn	product field rate	W
lapsed buying	bl	share of requirement	w/wp
lapsed rate	wl	sole buying	bs
light and heavy buying		sole rate	ws
		duplicate buying	bd
		duplicate rate	wd

3.3b Theoretical Comparisons

The empirical analyses are summarised in a series of tables in which observed figures are compared with theoretical predictions. Such comparisons are often criticised on the grounds that they contain no formal statistical measure of a goodness of fit. Some summary measures are used, namely the average deviation of results from the theoreticals. However, significance tests are not used to assess the size of any deviation. There are two main reasons why in using these models it is not the usual practice to discuss significance tests.

The main purpose in using these models is to provide generalisations across a series of samples, rather than to focus on one particular product field or region. Thus Ehrenberg and Goodhardt (1982 pages 19-20) note that this type of analysis,

"...differs from the main thrust of modern statistics. The emphasis is on generalisation across many different conditions of observation (eg different

brands, products, time periods, countries etc) rather than on inference from a single random sample to the specific population from which it was selected, or on estimating a previously unknown relationship in an isolated set of data."

The theme of generalisation arises in two ways in these analyses:

- * Does the model apply to private label purchasing patterns in the same way as is known to apply for a wider range of brands and more recently for stores?
- * When unusual or atypical results occur in the analyses for one product field, do they occur in other data sets?

Because of the second point, the consistency of results is stressed rather than just the size of any discrepancy. This is achieved by examining 5 product fields in two regions, which can be considered as 10 different samples. It is the regularity of results which is important, rather than whether they are significant in some statistical sense. Indeed the goodness of fit test is largely superceded by achieving the same objective empirically.

This emphasis on consistency finds support in a wider movement in statistics, which is related to exploratory versus confirmatory approaches to statistical analysis. Chatfield (1988 page 276) notes;

"Many analyses involve one or more significance tests. Most statisticians now agree that they are widely overused and also misused in many scientific areas....The two dicta which I like to stress are that ' a significant difference is not the same thing as an interesting difference'. It is usually desirable to see if interesting results are repeatable or generalisable to different conditions rather than to see if one particular sample is significant."

Moreover, the models are stochastic approximations to certain aspects of consumer behaviour. They do not mean that consumer purchasing behaviour is explained in some way by the Poisson-Gamma formulation or the Dirichlet formulation (as discussed in sections 3.4a and 3.5a). However, the models are useful and powerful applications since they provide a range of theoretical norms which help to structure large amounts of empirical data. Given this is the way the models are used, to set up formal statistical tests that the model

predictions are true/false, when compared against some observed data is really missing the point.

We now discuss the NBD and Dirichlet models in more detail; the theory, their assumptions, some interpretation and show a worked example of each.

3.4 THE NEGATIVE BINOMIAL DISTRIBUTION (NBD)

This distribution was first stated by Montmort in 1714 after Bernouilli's positive Binomial Distribution in 1713. The model has found many applications in accident statistics, contagious diseases and consumer behaviour (see for example, Irwin 1964, Kemp 1970). But it was Ehrenberg (1959) who first presented results showing that the NBD gave a good prediction of the frequency distribution of the total number of units bought by members of a consumer panel.

Later the model was used to predict the number of purchase occasions in a period as suggested by Grahn (1969) instead of the number of units bought in the analysis period - the fit was found to be even better (Chatfield and Goodhardt 1970).

The NBD is a purchase incidence model which has two components. A model of the incidence of an individuals (or households) purchase events, and a model in which the parameters of this purchase incidence model vary over the population. The NBD is always positively skewed with one mode at zero.

3.4a The Theory

There are several stochastic processes which can give rise to an NBD formulation, as discussed by Anscombe (1950). One example being that purchasing occasions are still distributed as a Poisson distribution, but that the distribution is the same for all consumers, and that amounts bought per occasion are distributed as a logarithmic series distribution. This was discussed by Williamson and Bretherton (1964) in the context of industrial purchasing. It was suggested by Professor Cramer (1965) as a possible model for consumer goods purchasing. However, the model is not consistent with empirical findings because different consumers average purchasing patterns are not the same.

In the case of predicting buyer behaviour, Ehrenberg suggests the NBD can be derived from assumptions that the stochastic process which generates purchases in individual unit time periods is Poisson. And that longer run average purchasing rates across the population of consumers may be described by a

Gamma distribution. The evidence in analysing purchasing behaviour under stationary conditions points to this formulation (Ehrenberg 1988).

The resulting model is two dimensional; one being time, the other (an unordered one), individual consumers. This is shown schematically in Table 3.3.

Table 3.3 : A Stochastic Model Over Time Yielding The NBD In Any Given Time Period

	Successive Time Periods					Long-run Averages	Horizontal Distribution
	1	2	3	4	n		
Consumers :							
a	*	*	*	*	*	u	poisson
b	*	*	*	*	*	u	poisson
c	*	*	*	*	*	u	poisson
d	*	*	*	*	*	u	poisson
.							
.							
n	*	*	*	*	*	u	poisson
Mean	m	m	m	m	m	m	
Vertical Distribution	NBD	NBD	NBD	NBD			gamma

Note : The * values in the body of the table represent varying observed numbers of purchases and are not intended to imply equality (Ehrenberg 1988 page 61).

The Poisson and Gamma formulations are discussed below.

The Poisson Formulation

For individual purchase sequences this is a plausible a-priori assumption under two conditions which should be more or less satisfied under normal circumstances (Ehrenberg 1988 pages 61-3). The model requires the purchase frequencies to behave like independent random samplings from a system where the purchase probabilities are constant for each individual at any given point in time. And where probabilities are independent of each other. This means

that purchasing is like the fall of raindrops; we cannot predict when the next raindrop will strike from when the last one fell, and we can not predict when the next purchase will be made from when the last one was made. This is essentially the Poisson assumption. The two conditions are:

- 1 Not only must successive time periods be of equal length, but they must be similar to each other. For example, with fast moving consumer goods, weeks must be used rather than days. Shopping on Mondays differs to that on Saturdays and hence tends to be non-stationary. In a longer period though, such short term time effects may not surface or be balanced out. This is the stationarity condition.
- 2 The period of analysis must be sufficiently long so that purchases made in one period do not directly affect those in the next. So for example, a product must be more or less used up before another purchase is contemplated. This is the minimum time interval condition.

These are usually found to exist in practice. However, some criticism has been made of the NBD assumptions. First, that real consumers purchase more regularly than the NBD's Poisson (random) purchasing assumption because if people consume goods in a regular fashion, then we would expect them to also purchase them in a regular fashion. Secondly, that purchase incidence should not be independent of the time elapsed since the previous purchase as people are less likely to shop again immediately after completing a shopping trip.

As a result there have been a number of attempts to allow the propensity to purchase to depend on the time elapsed since the previous purchase. Most of these have focussed on the use of probability distributions which are more regular than the exponential to model the interpurchase times at household level. The Erlang distribution, usually of order 2 (a Poisson with every other reading censored) or more, corresponds to purchases which are more regular than Poisson and to a propensity to purchase which has the required time dependency. Studies by Herniter (1971), Chatfield and Goodhardt (1973), Zufryden (1978), Jeuland, Bass and Wright (1980), and Gupta (1988) have shown that the Erlang family of distributions provide a better description of households inter-purchase times than the exponential. Other studies have used Gaussian distributions (Banerjee and Bhattacharyya 1976), lognormal distributions (Lawrence 1980) which have also shown to be a good fit.

Another criticism is that peoples' purchase rates are not constant over time because of marketing effects, and the fact that people move in and out of product categories due to boredom and life style changes. Some early work has been undertaken to show how such marketing variables affect the interpurchase time but results are inconclusive (Neslin, Henderson and Quelch 1985, Gupta 1988).

However, in practice these modifications have not improved the model fit sufficiently to warrant the added complexity (Chatfield and Goodhardt 1973).

The Gamma Formulation

Some customers purchase frequently, others hardly at all. The Gamma describes this heterogeneity in purchasing rates across the population. The Gamma assumption relates to the distribution of mean values for different consumers. Two conditions must hold:

- 1 That different consumers buy the given brand independently of buying each of the other brands in the market.
- 2 Consumer buying of the brand is independent of how much of the total product class the consumer purchases.

This means that item purchases by each potential buyer are "as if" random over time and independent of each other. Each consumer has an average frequency of purchase, and these (the means of the Poisson) follow a Gamma distribution with parameter k across the whole population.

The main justification for using the Poisson-Gamma formulation is that it holds well in practice and does so under many different conditions. Though much work has been undertaken on these assumptions, none of alternative formulations have been so successful as to make the original specification redundant (Chatfield and Goodhardt 1973) and furthermore, none have been so extensively generalised.

Without explanation, the NBD model can appear abstract. However, its assumptions can be interpreted and related to actual buying behaviour. Why does the Poisson-Gamma formulation describe peoples' buying behaviour?

The stationarity assumption has two implications on buying behaviour:

First, it means that each individual has constant purchase probabilities over the analysis period, but these vary across individuals. People have preferences and these are reflected in their somewhat habitual purchase behaviour, which varies little in the short-term. Some buyers prefer one item, others prefer another, but rarely to the exclusion of all other items available. So each person has their own repertoire from which to choose and this remains relatively unchanged in the short term.

There are occasions when this does not hold. For example, during a new brand launch, individual purchase probabilities are revised so as to accommodate the new offering (Wellan and Ehrenberg 1988, Wellan 1985). Under these changing conditions there is some evidence that the fit of the model maybe poorer, but as soon as a new equilibrium is reached (which it usually is), the model fit improves.

Secondly, it means that time periods under investigation must be sufficiently long to overcome any short term changes, they must be similar and allow sufficient time for the item to be used up. Groceries are usually purchased every week, so this is the minimum time period analysed. Furthermore, we find that shopping behaviour differs depending on the day of the week. Therefore by taking a week as the minimum time period, this sort of short term non-stationarity is smoothed out.

The assumptions of the gamma part of the NBD relate to consumer heterogeneity. Individuals differ in their purchasing habits. Some are heavy buyers of an item and light buyers of another, whilst the opposite occurs for other consumers. Indeed, for each item, there is a similar division of light, medium and heavy buyers. Furthermore those households who are heavy buyers of an item, are not necessarily heavy buyers of another.

Both assumptions relate to individual purchase behaviour, but the NBD model describes purchasing at the aggregate consumer level. Though individuals all have their own preferences and are affected differently by the various marketing activities, the aggregate picture is somewhat simplified. In the aggregate, the effects of different marketing activities coupled with inherent differences between individuals brand preferences, are sufficiently irregular,

that they can be described "as if" they were stochastic. This does not mean that we believe there are no causes, rather that the sum total of all the varying and dynamic inputs can be modelled as if the resulting aggregate behaviour is stochastic.

3.4b The Mathematics

Only the basic mathematics are outlined here, for derivations and more details see Ehrenberg (1988 chapter 7 and appendix A). The NBD is a two parameter discrete distribution of non-negative integers. If the two parameters are taken to be the mean m , which is the mean number of purchases made by all consumers in a given time period; and exponent k , which is the parameter of the Gamma distribution which describes differences in average purchasing rates of different consumers, the probability $p(r)$ of making r purchases is :

$$p_r = \left(1 + \frac{m}{k}\right)^{-k} \frac{\Gamma(k+r)}{\Gamma(r+1)\Gamma(k)} \left(\frac{m}{m+k}\right)^r. \quad (1)$$

m varies in proportion to the unit time periods, whereas k is constant for different length time periods. Most of the repeat buying formulae depend explicitly on k being constant in this way and this is important to the validity of the NBD model.

The probabilities derive from the expression of the binomial process

$$\left(1 - \frac{m}{m+k}\right)^{-k} \quad (2)$$

in which the exponent k has a negative sign. It is however suggested that it is more convenient to use the parameter $a = m/k$ instead of k . So

$$\left(1 - \frac{a}{1+a}\right)^{-k}. \quad (3)$$

The mean and variance of the distribution are given respectively by:

$$E(r) = m = ak \quad (4)$$

$$\text{Var}(r) = m(1+a) = ak(1+a) \quad (5)$$

The NBD is always positively skewed with one mode at zero. This is observed to be generally true for purchasing patterns from consumer panel data.

The NBD can also be generalised so that purchasing patterns in more than one time period can be represented by formulating the NBD as a multi-variate NBD. For a fuller discussion of the mathematics involved see Ehrenberg (1988 page 131).

3.4c Fitting the NBD

First, the formulae are introduced and these are applied in section 3.4d.

Two values, m and k need to be estimated to solve equations 4 and 5. The best estimate of m is the observed sample mean, which is readily available from panel data. However, k is more difficult to estimate. There are various ways of achieving this but one way is to compute a new quantity, c and then calculate $a=m/k$.

$$c = -m/\ln p(0) \quad (6)$$

and make use of the pre-prepared tables (Ehrenberg 1988 page 328).

We need to calculate the penetration (b) and purchase frequency (w) from our panel data to calculate the two parameters. T refers the unit length time period.

$$b = 1-p(0) = 1-(1+a)^{-k} \quad (7)$$

$$w = m/b \quad \text{since} \quad m=b*w \quad (8)$$

Following from the estimation of a and k , the theoretical probability of a household buying once, twice and r times in a given time period can be calculated from $p(r-1)$ by the recursive formula;

$$p_r = \left(\frac{a}{1+a}\right) \left(1 - \frac{a-m}{ar}\right) p_{r-1} \quad (9)$$

The NBD can also be used to provide estimates of penetration and average purchase frequency over periods of varying lengths. Under stationary market conditions, the average number of purchases per household m , would be the same in periods of identical length. Therefore, the value of m in any time period must be proportional to its length.

If mt is the mean number of purchases per household in a period of length T , then under steady state conditions;

$$m_T = Tm. \quad (10)$$

Furthermore the value of the parameter k is independent of the length of the time period. If values of $a = Tm/k$ and mT are substituted into equations 7 and 8 then;

$$b_T = 1 - (1 + Tm/k)^{-k} \quad (11)$$

and

$$w_T = \frac{Tm}{\{1 - (1 + Tm/k)^{-k}\}} \quad (12)$$

where b_T = the penetration in period of length T relative to the unit length base period

and w_T = the average number of purchases per buyer in the period of length T

The NBD can also be used for repeat buying. This is the main area for which it is used in the thesis and a worked example is shown in section 3.4d. This is essentially examining purchasing in two equal length time periods which need not necessarily be in consecutive order.

The following notation is necessary for further discussion;

- b = proportion of people buying at least once
- br = proportion of the population buying in both periods 1 and 2
- bn = proportion of the population buying in period 2 but not 1
- bl = proportion of the population buying in 1 but not 2

Under steady state conditions we have the following;

$$bn = b - br \quad \text{and} \quad (13)$$

$$bl = bn \quad (14)$$

since b is the same in any two periods of equal length.

Assuming that the base period is of unit length $T=1$, the length of the combined periods 1 and 2 will be $T = 2$. Substituting this into equation 11 we obtain;

$$b_2 = 1 - (1+2a)^{-k} = 1 - (1+2a) \quad (15)$$

and since

$$br = bn - b$$

$$bn = br - b$$

$$br = (br - b) - b$$

$$br = br - 2b$$

$$br = 2(1 - (1+a)^{-k}) - (1 - (1+2a)^{-k}) \quad (16)$$

$$br = 1 - 2(1+a)^{-k} + (1+2a)^{-k} \quad (17)$$

Taking this as the proportion of all buyers b , gives the proportion of those buying in the second period who also bought in the first.

Similarly for purchasing rates we have;

the number of purchases made by repeat buyers expressed on a per informant basis is

$$\begin{aligned} m_R &= m \{1 - (1+m/k)^{-k-1}\} \\ &= m \{1 - (1+a)^{-k-1}\} \end{aligned} \quad (18)$$

So the rate of buying by repeat buyers is

$$w_R = m_R / b_R \quad (19)$$

Similarly for new buyers. On a per informant basis, the rate of new buying is,

$$m_N = \frac{m}{(1+a)^{k+1}} \quad (20)$$

So the buying frequency given the proportion of new buyers is $bn = b - br$ is,

$$w_N = m_N / b_N, \quad (21)$$

$$b_N = b - b_R. \quad (22)$$

3.4d An Example - Repeat Buying Of A Brand

The model requires the penetration and purchase frequency of each brand as input. These drive the model, along with the 2 parameters. The theoretical incidence and rate of repeat buying for a brand of Fruit Squash in the London region for the average of two 24 week periods are calculated below to show the method and input requirements.

Input data (observed): $b = 0.134$ $w = 2.8$

m	=	mean number of purchases per household	b^*w	=	0.375
$p(0)$	=	proportion of non-buyers	$1-b$	=	0.866
c	=	used to help find "a"	$m/\ln(p0)$	=	2.61
a	=	model parameter (from Appendix 5)	m/k	=	4.4
k	=	model parameter	m/a	=	0.085

The incidence of repeat buying is calculated as follows:

$$br = 1 - 2(1+a)^{-k} + (1+2a)^{-k} \quad (17)$$

by inserting the above observed figures we obtain

$$br = 1 - 2(5.4)^{-k} + (1+8.8)^{-k} = .091$$

The ratio of those repeat buying in both periods to those who bought in the first 24 week period is br/b

$$br/b = .091/.134 = .68$$

Therefore 68% of buyers in the first time period are expected to buy in the next 24 week period.

The rate of repeat buying is calculated as follows:

$$wr = mr/br \quad (19)$$

Where mr is the number of purchases made by repeat buyers expressed on a per informant basis

$$mr = m \{1 - (1+a)^{-k-1}\} \quad (18)$$

$$mr = .375(1-(5.4)^{-1.085}) = 0.314$$

As $wr = mr/br$ then

$$wr = .134/.09 = 3.5$$

Therefore, 68 % of Squash buyers are expected to buy again in the next 24 week period and to do so nearly 3.5 times.

For new and lapsed buyers the logic is the same as above.

In summary, the NBD is a simple stochastic model which has proved successful in describing buyer behaviour. It is based on 2 parameters, both of which are easily obtained from panel data. This makes the practical application of the model much easier than some other stochastic models. Many more statistics are available from the model but we only use the repeat buying and purchase frequency distribution measures directly in the thesis.

The fundamental property of the NBD is the purchase frequency distribution of light, medium and heavy buying. This is also used as the basis for the Dirichlet model which we now discuss.

3.5 THE DIRICHLET MODEL

This was first developed by Chatfield and Goodhardt as an integrated brand choice and purchase incidence model. (For a full discussion see Goodhardt et al 1984, Ehrenberg 1988 Chapter 13). It is a multivariate stochastic model capable of describing both brand choice and purchase incidence under stationary conditions in an unsegmented market. (An unsegmented market refers to one where all brands compete equally with one another.) This is a common situation where over the time periods analysed, sales of each brand show little variation, and different brands show no special groupings.

The model can specify the number of product class purchases each consumer makes in a particular time period, and the probability with which each consumer chooses a brand from those available.

3.5a The Theory

The model assumes a mixture of distributions at four levels when applied to multi-brand buying behaviour (Ehrenberg 1988 page 255) :

- 1 Purchasing of the product class takes the form of a **Poisson** process for each consumer.
- 2 The purchasing rates of different consumers follow a **Gamma** distribution.
- 3 Each consumer's choice among the available brands follow a **multi-nomial** distribution.
- 4 These choice probabilities follow a multi-variate **Beta or Dirichlet** distribution across different consumers.

The following assumptions deal with each component of the model. The model formulation is such that it specifies a probability vector for a consumer making any combination of purchases from items in an analysis period of given length. Summing over all items gives the total number of product class purchases made by the consumer in that period.

There are 5 assumptions in all, the first two relate to purchase incidence within a product class ie the Poisson and Gamma parts of the model.

1 Poisson

If the *i*th individual behaves as if stochastic, successive purchases are assumed to be independent with a constant mean rate in a given time period. The minimum inter-purchase time is usually a week with grocery products. The number of purchases made in each consecutive period is a Poisson distribution.

2 Gamma

The mean purchasing rates vary between individuals according to a Gamma distribution.

These state that the number of product purchases made by all individuals in a given length time period follows an NBD.

The next two concern brand choice, ie the Dirichlet part of the model

- 3 The i th individual's brand choices over a succession of purchases are as if stochastic, with a probability $(p_j)_i$ of choosing brand j from those available. These probabilities are fixed over time and brand choices at successive purchases are assumed to be independent. The number of brand purchases that the individual makes in a sequence of n purchases can be modelled by a multinomial with parameters $n_{ij}(p), \dots, (p_g)$ (Wilkes 1962, page 139).
- 4 These probabilities $(p_j)_i$ vary among individuals according to a Dirichlet distribution. This is the multivariate Beta-distribution. The probability of choosing brand j has the j th marginal distribution. This is the simple Beta distribution, with its mean equal to the brands market share.

Together they state that the joint distribution of purchases of different brands across all consumers is given by a mixture of multinomials with a Dirichlet distribution. (When $g=2$, this reduces to the Beta-Binomial distribution).

The final assumption concerns the relationship between these four ie purchase incidence and brand choice. This concerns the multinomial part of the model.

- 5 The brand choice probabilities and average purchase frequencies of different consumers are distributed independently over the population.

These assumptions are sufficient to specify a single model, the NBD Dirichlet or Dirichlet for short.

The main justification of the Dirichlet model is that in practice it fits many different aspects of buyer behaviour under a wide range of conditions. Though it is not as well tested as the NBD model, the Dirichlet has successfully described the patterns of buyer behaviour in a selection of product fields (Ehrenberg 1988). In addition there are reasons why the specific distributions of brand choice and purchase incidence should be as outlined above rather than some other specification. These are discussed below.

Purchase Incidence Assumptions

The first assumption rests on the basic observation that purchase incidence tends to be effectively independent of the incidence of previous purchases, and sufficiently irregular that it can be regarded as if stochastic. The Poisson

remains a workable approximation to this, although various alternatives have been discussed as noted on page 56 (Chatfield and Goodhardt 1973, Herniter 1971, Gupta 1988, Jeuland et al 1980, Zufryden 1978, Lawrence 1980).

The second is justified because if, for different product classes, the average purchase rate is independent of the rates for other products and the proportion of a consumer's total purchases is independent of the rate of purchasing all products, then the distribution of mean rates of purchasing must be Gamma. This is approximately so in practice where heavy buyers of one product field are not necessarily heavy buyers of another (Goodhardt and Chatfield 1973). These were discussed more with respect to the NBD (see page 56).

Brand Choice Distribution Assumptions

The lack of segmentation in the market implies that choosing between different brands should be more or less independent. An unsegmented market means that the proportion of purchases devoted to any one brand is independent of the way the remaining purchases are distributed between other brands.

The Dirichlet distribution is therefore the quantitative analogue of the marketing criterion of non-segmentation. In a strictly non-segmented market where the multinomial choice probabilities are fixed over time, the Dirichlet distribution is the only possible model for brand choice.

The last assumption has some empirical support (Shoemaker et al 1977), but more work is needed here (Sabavala 1988).

The Dirichlet model can appear abstract in relation to peoples' buying behaviour. Why do these assumptions describe buying patterns so well?

The stationarity and heterogeneity assumptions have similar implications as discussed for the NBD model previously. In addition it is assumed that the market is unsegmented. Though much of the marketing literature suggests fast moving consumer goods markets are segmented (Mordern 1985, Yankelovich 1964), we find that in practice this is not the case (Ehrenberg 1988, Ellis and Uncles 1989 Appendix 12). Indeed, we show in the empirical sections (4.2d, 5.5 and 6.3d) that differences in the way people buy brands and private labels

within a product field are usually quite small, and buying one item is usually approximately independent of buying another.

If there is evidence of clustering on any other principle than market share this would show through as a deviation from the theoretical predictions. We show that items are bought as though the only difference between them was their market share level to a first order of approximation. This has implications on traditional marketing theories of market segmentation and competition which we discuss in chapter 9.

More detailed interpretation of these models is left for the final discussion in chapter 9. This serves only as an introduction.

3.5b The Mathematics

Here we consider a population of N consumers making purchases in a product class of g brands. The Dirichlet model specifies probabilistically how many purchases each consumer makes in a given time period, and which brand is bought on each purchase occasion. It combines both the purchase incidence and brand choice aspects of buyer behaviour into one model.

The number of purchases an individual (or household) makes of each of the g brands in a period of length T is given by a g -variate discrete random variable with the joint frequency distribution;

$$[\mathcal{M}(\mathbf{r} | \mathbf{p}, n) \wedge \mathcal{D}(\mathbf{p} | \boldsymbol{\alpha})] \wedge \frac{1}{n!} [\mathcal{P}(n | \mu) \wedge \mathcal{G}(\mu | MT, K)] \quad (24)$$

where \mathcal{M} , \mathcal{D} , \mathcal{P} and \mathcal{G} denote the Multinomial, Dirichlet, Poisson and Gamma distributions.

3.5c Fitting The Dirichlet

First the values of $\alpha_1, \alpha_2, \dots, \alpha_g$, assumption 4, and the parameters M and K of assumption 2 need to be estimated. Then we can calculate the theoretical value of any specific aspect of buying behaviour such as penetration or purchase frequency. (Capitals indicate product class parameters and small letters refer to brand parameters.)

Once the parameters have been estimated, the theoretical value of any specific aspect of buying behaviour can be calculated. The calculations are straight

forward in principle but computationally tedious. The main simplification is to reduce the calculations down to those of the Beta-Binomial distribution. Here in calculating for a specific brand j with brand share α_j/S , we combine all other brands into a single superbrand with brand share $(S - \alpha_j)/S$. This means the probability of making r purchases of brand j , conditional on n purchases of the product class having been made ($r_j \leq n$), is given by the Beta-Binomial distribution

$$p(r_j | n) = \binom{n}{r_j} B(\alpha_j + r_j, S - \alpha_j + n - r_j) / B(\alpha_j, S - \alpha_j) \quad (25)$$

where B denotes the Beta function.

The proportion of consumers buying the product-class n times and buying brand j r_j times is then given by the product of the equations for P_n and $p(r_j | n)$

$$p(r_j, n) = P_n p(r_j | n) \quad (26)$$

By summing $p(r, n)$ over appropriate values of n and r , we can calculate any statistic of interest for the brand. Summations over the values of n need to be truncated because the NBD probabilities of buying the product class form an infinite series. This is achieved by an appropriate recurrence relation or some ad-hoc truncation procedure.

Only formulae for those measures used in the example are shown below. For more information see Ehrenberg (1988 Chapter 13).

The penetration b of brand j is estimated as $(1 - p(0))$, the proportion not buying the brand, where

$$p(0) = \sum_{n=0}^{\infty} \{P_n p(0 | n)\} \quad (27)$$

and $p(0|n)$ is the probability of making zero purchases of brand j given that n purchases of the product class have been made in the analysis period. The summation is truncated. Here $p(0|n)$ is from the Beta-Binomial, writing α for α_j ,

$$p(0 | n) = \frac{(S - \alpha)(S - \alpha + 1) \dots (S - \alpha + n - 1)}{S(S + 1) \dots (S + n - 1)} \quad \text{for } n \geq 1 \quad (28)$$

$$p(0 | 0) = 1$$

$$P(0/0) = 1$$

The theoretical number of purchases of brand j per buyer is calculated as

$$w = \sum_{n=1}^{\infty} \left\{ P_n \sum_{r=1}^n r p(r|n) \right\} / [1 - p(0)] \quad (29)$$

and their average number of product class purchases is,

$$w_p = \sum_{n=1}^{\infty} \{ n P_n [1 - p(0|n)] \} / [1 - p(0)] \quad (30)$$

The proportion who buy brand j only (sole buyers) is given by a computationally very effective short cut

$$\sum_{n=1}^{\infty} \{ P_n p(n|n) \} \quad (31)$$

since if they buy the product n times, they must be buying the brand n times also. Their average purchase frequency per buyer is

$$\left\{ \sum_{n=1}^{\infty} \{ n P_n p(n|n) \} \right\} / \left\{ \sum_{n=1}^{\infty} \{ P_n p(n|n) \} \right\} \quad (32)$$

In different time periods, the above formulae remain the same except that M in the NBD equation becomes MT.

To estimate the number of repeat buyers from one time period of length T to another of equal length we enumerate b T for the double period and b for a single period, and calculate $2b - b$. However, at this time there is no simple method for calculating the theoretical average purchase frequency for repeat buyers. Instead the NBD is generally used.

3.5d An Example

Before we begin to examine buyer behaviour measures, three areas which deal with the theoretical model need to be set up. First we have to input the values for the distribution of purchases of the product field as a whole, then estimate the structural parameter S, and thirdly estimate the Dirichlet probabilities. These are detailed in turn below for Quosh, a brand of Fruit Squash in the London region.

Since the NBD is an infinite distribution, it is strictly impossible to calculate all these values of $P(n)$ numerically. An ad-hoc truncation where the calculations are cut-off at some point in the distribution is usually adopted.

Computer routines are used to provide an approximate estimate for the tail of the NBD distribution. These tails are numerically more important than they may seem at first because they consist of very heavy buyers. However, because our purpose here is to show an example, the rather complex truncation procedure is not shown. For details see a method developed by Gerald Goodhardt see Ehrenberg 1988. Instead of truncating the distribution at some point, calculations cease when the number of purchases reaches 20. There is therefore a shortfall of buyers which affects the theoretical estimates. These differ somewhat from those in chapter 4 which were derived using the software package where the Goodhardt truncation method is adopted. However, for the purposes of outlining the mathematical procedure, this difference is of no consequence.

b) Estimating The Dirichlet Parameter \hat{S}

The \hat{S} parameter reflects one dimension of consumer diversity. It is estimated from calculating \hat{S}_j values for each item and then obtaining an overall estimate by a weighted average (by market share) across all items in the product field. It provides a diagnostic check on cases where the model fails to fit a particular item and these can be left out of the weighted average if required.

Input Statistics:

	W,w	B,b	p(0)	M,m
Product field	6.21	.6077	.3923	3.77
Brand - Quosh	2.76	.134	.866	.37

The estimate of \hat{S} for an item has to be by iteration as there is no explicit algebraic formula.

We begin with a reasonable estimate, say $S'=2$. The objective being to find an estimate such that the predicted number of non-buyers of the brand $p'0$ is equal or close to the observed $p0$.

Two measures c' and d' are used to help in the iteration, although they have no real meaning. On each iteration, the items are adjusted to take account of the new information.

$$c' = S' - ((m * S')/M) = 2 - (.37 * 2) / 3.77 = 1.8 \quad (34)$$

$$d' = c' / S' = 1.8 / 2 = .9 \quad (35)$$

p_0 and p_1 are used to derive the first estimate of p'_0 for $S'= 2$

$$P'_0 = P_0 + (P_1 \times d') \quad (36)$$

$$= .3923 + (.142 * .9) = 0.5201$$

Next we use P_2 , still keeping $S'= 2$. The value of d' has to be raised and the sum for p'_0 is adjusted.

$$\begin{aligned} \text{New } d' &= \text{old } d' * (c' + (n-1) / S' + (n-1)) \quad (37) \\ &= 0.9 * (1.8 + (2-1) / 2+1) = 0.84 \end{aligned}$$

$$\begin{aligned} \text{New } P(0) &= \text{old } p'_0 + (P_2 * d') \quad (38) \\ &= .5201 + (.0899 * .84) = .596 \end{aligned}$$

This continues until the cut-off point is reached. Then depending on whether the estimated p'_0 is greater or smaller than the observed p_0 , the S' value is adjusted. If p'_0 is greater than p_0 , the S' value is increased and vice-versa.

The computer iteration continues until the S' for Quosh is 1.7343. The remaining items in this product field are all found in the same way (Table 3.3).

Table 3.4 : S Values For Individual Brands

Total private label	0.7
Robinsons	2.1
OB	3.5
Quosh	1.7
Kia	3.1
RB	1.9
Corona	0.7
Wells	2.7

Values of S vary from 0.7 to 3.5. This degree of variation is small and so the model fit should be good. However, there is little documented evidence of how the \hat{S} value varies.

The overall Dirichlet parameter S is then a weighted average of these individual \hat{S}_j obtained by taking the market shares m_j into account.

$$\hat{S} = \frac{\sum_j (\hat{S}_j m_j / M)}{\sum_j (m_j / M)} \quad (39)$$

This yields the following for each item (Table 3.4).

Table 3.5 : Overall Dirichlet Parameter

Brand	m_j (ie $b \cdot w$)	m_j / M
Total pl	2.1	0.55
Robinsons	0.6	0.14
OB	0.3	0.08
Quosh	0.4	0.01
Kia	0.2	0.06
RB	0.2	0.05
Corona	0.1	0.02
Wells	0.3	0.07
Total		1.07 *

* This should be approximately equal to 1 because the full data set has been used.

$$\begin{aligned} \hat{S} &= (0.7 * 0.55) + (2.1 * 0.14) + \dots + (2.7 * 0.07) / .m_j / M \\ \hat{S} &= 1.5146 \end{aligned} \quad (40)$$

The Matrix Of Proportions

There are no explicit algebraic formula relating say B and W to S. So a matrix of proportions for all those making n purchases of the product and r purchases of each item is calculated. From these statistics, the various buyer behaviour statistics for each item can finally be derived.

Only part of the matrix is shown (Table 3.6) with an example of how the figures are derived. The proportions buying in the second line are for the whole product field. The body of the table represents the proportion of the population making n purchases of Fruit Squash and r purchases of Quosh.

Table 3.6 : Matrix Of Dirichlet Proportions For A Single Brand Quosh (London)

Purchases of the Product:						Total
Numbers	0	1	2	3	n	
Proportions	P0	P1	P2	P3	Pn	1.0
	.392	.142	.09	.07	..	
Purchases of the Brand:						
0	p00	p01	p02	p03	..	p0
	.392	.128	.076	.005	..	.800
1		p11	p12	p13	..	p1
		0.14	.009	.0007	..	.003
..						..
r						pr

The row labelled "0" represent the proportions not buying the Quosh brand. For example, 39% of buyers did not purchase Quosh in 24 weeks. These values are calculated by the recurrence formula;

$$P_{0n} = P_{0(n-1)} \times \frac{(\beta + n - 1)}{(\hat{\alpha} + \beta + n - 1)} \times \frac{P_n}{P_{(n-1)}} \quad \text{for } n = 1, \dots, n' + 1. \quad (41)$$

$$\text{where } \hat{\alpha}_j = S(m_j/M) \quad (42)$$

$$= 1.5146 * 0.098 = 0.148$$

$$\beta_j = S - \hat{\alpha}_j \quad (43)$$

$$= 1.5146 - 0.148 = 1.3666$$

$$p_0 = 0.392$$

Therefore

$$P_{01} = 0.392 * [(1.367 + 1 - 1) / (0.148 + 1.367 + 1 - 1)] * .142/.392$$

$$P_{01} = 0.128$$

$$P_{02} = 0.128 * [(1.367 + 2 - 1) / (0.148 + 1.367 + 2 - 1)] * 0.089/0.142$$

$$P_{02} = 0.0763$$

This continues until the whole of the non-buyer row is filled. Entries to the left of the leading diagonal are all zero. The remaining entries to the right of the diagonals are found by another recurrence formula.

$$P_{rn} = \frac{(n-r+1)}{r} \times \frac{(\hat{\alpha} + r - 1)}{(\hat{\beta} + n - r)} \times P_{(r-1)n}, \text{ for } r = 1, \dots, r' + 1, \quad (44)$$

The starting values P_{1n} are obtained from the proportions p_{0n} in the first row as follows.

$$p_{11} = [(1-1+1)/1] * [(0.148 + 1 - 1) / (1.3666 + 1 - 1)] * 0.128$$

$$p_{11} = 0.0139$$

$$p_{12} = [(2-1+1)/1] * [(0.148 + 1 - 1) / (1.3666 + 2 - 1)] * 0.0763$$

$$p_{12} = 0.00954$$

This continues until the matrix is complete whereupon the buyer behaviour statistics of interest can be calculated. Some examples are shown below, but for more details see Ehrenberg (1988 Appendix C).

Calculation Of Some Buyer Behaviour Statistics

Penetration And Purchase Frequency

Penetration = $1 - p(0)$ where $p(0)$ is the total of the non-buyers row, 0.80

$$\hat{b} = 1 - 0.80 = 0.20$$

Purchase frequency = $m_j/b = .369 / 0.20 = 1.8$

It is estimated that 20% of buyers will buy Quosh 1.8 times in 24 weeks.

Total Product Purchase Rate

$$\hat{w}_p = \{1(P_1 - P_{01}) + 2(P_2 - P_{02}) + \dots + (n'+1)(P_{n'+1} - P_{0(n'+1)})\} / \hat{b}$$

$$\hat{w}_p = 1(.142 - .128) + 2(.0899 - .0763) + \text{etc}$$

$$\hat{w}_p = 1.88 / 0.20 = 9.4$$

Quosh buyers make over 9 Squash purchases in 24 weeks.

Sole Buyer

$$\delta_s = p_{11} + p_{22} + \dots + p_{(r'+1)(n'+1)}$$

$$bs = 0.014 + 0.004 + \dots + P_{nn}$$

$$bs = 0.03$$

expressing this as a percentage of all buyers

$$\delta_s / \delta = 0.03 / 0.20 = 0.10$$

$$\hat{\phi}_s = \{ 1 \times p_{11} + 2 \times p_{22} + \dots + (n'+1) \times p_{(r'+1)(n'+1)} \} / \delta_s$$

$$ws = [1(0.14) + 2(.004) + \dots \text{etc}] / \hat{bs}$$

$$ws = 0.06 / 0.02 = 2.0$$

10% of Quosh buyers remain completely loyal to this brand during a 24 week period and make 2 purchases.

Therefore in summary, the Dirichlet has proved successful in describing buyer behaviour in a variety of product fields, though it is less well tested than the NBD. It is a multi-variate stochastic model based on $g-1$ parameters, all of which can be derived from panel data. The model is capable of providing many buyer behaviour statistics for individual items and the product field. These are all used directly in the thesis, being calculated using the computer software package BUYER (Uncles 1988).

3.6 STATIONARITY AND MARKET SEGMENTATION

Before we use the models for our empirical analyses, we need to briefly discuss the assumption of stationarity which is inherent in both the NBD and Dirichlet models, and market segmentation which is inherent in the Dirichlet model. More details of these are provided in Chapter 8.

3.6a Stationarity

A number of theoretical assumptions are made in the NBD and Dirichlet models, one of which is stationarity. Stationarity, in the sense used here, is the absence of any marked short-term sales trend for the item or market in question. It does not necessarily mean a lack of changing conditions, or the absence of trends for other brands, but that the sum total of all varying and dynamic inputs, advertising, pricing and promotions, have no overall effect on the item or market in question, in the relevant time period.

This may seem somewhat counter-intuitive because marketing activities are usually designed to induce non-stationarity in consumers purchase behaviour.

Indeed, given the usual level of promotional activity in fast moving consumer goods markets, any predictive test of the NBD requires either an assumption of stationarity or some means to control for its variation (Montgomery 1988, Sabavala 1988). However, before we start to try and control for stationarity, we need to see how non-stationarity actually affects the NBD predictions.

Little substantive work has been undertaken on the matter, indeed research results on this have shown that the model still works reasonably well to a first order of approximation (Wellan 1985, Wellan and Ehrenberg 1987). Furthermore, though individual purchase behaviour may be affected in this manner, the point is that in the aggregate such effects at the individual level may cancel each other out over time.

Because the theoretical estimates are used as a benchmark against which all results are compared and interpreted, it is important to ensure that either the assumptions are fulfilled in practice, or at least to be aware when they are not.

In an ideal situation, the model would describe the observed data exactly, and the model assumptions would be fulfilled. However, in reality, markets are not quite stationary and some forms of non-stationarity can cause problems in using the theoretical estimates as norms.

Movements around a steady base line do not usually produce major deviations from the theoretical predictions (Ehrenberg 1988). For example, sales fluctuate over time as marketing activities are undertaken. However, this is not usually a problem because data are aggregated into sufficiently long time periods so as to smooth out short-term fluctuations. In longer time periods, data are on the whole steady as we show in chapter 8. Though this type of non-stationarity exists in most product fields in reality the models can still be used.

It is only when movements are consistent and sizeable that problems can occur in using these models. One form of non-stationarity which can cause deviations from theoretical estimates is seasonality. For example, Fruit Squash has a summer (May to August inclusive) seasonal peak and sales rise during this period; Baked Beans by contrast have lower sales during the summer season.

Yet the effects of seasonality are not particularly noticeable in the analyses as

the base period for the model predictions is the average of two 24 week periods. Because the seasonal periods for the two product fields fall in the middle of the year, each 24 week period has a similar sales level. The 24 week base period essentially smooths out the effects of seasonality on the model predictions which is why there are no noticeable differences between seasonal and non-seasonal product fields. This is discussed in more detail in chapter 8.

So meaningful conclusions can still be drawn from model comparisons despite using seasonal data. Indeed the assumption is not as limiting as it may seem initially for three main reasons. First, the focus of the thesis is on how people buy private labels in comparison with brands. Seasonality only affects this comparison if it affects brands and private labels differently. Analyses show this is not the case (Chapter 8) and so no bias is introduced into the main comparison. A deviation which affects brands and private labels in a different way would show up over and above the seasonality deviation. Secondly, results are only of consequence in this study if they can be generalised across many product fields. Third, we know something of the way in which seasonality affects buying patterns and this can be taken into consideration in interpreting the results (Wellan 1985).

Therefore, theoretical estimates can still be used as yardsticks against which the data are compared. Indeed the fact that a result exists in both seasonal and non-seasonal product fields enhances its robustness.

3.6b Market Segmentation

The Dirichlet model assumes a non-segmented market where all items compete equally with each other, and the proportion of purchases devoted to any one item is independent of the way remaining purchases are distributed between other items.

We have some empirical evidence to show that this assumption is largely fulfilled in practice. This is discussed in more detail in chapter 8.

The model assumptions have been largely fulfilled in practice and even when violations occur, they do so across the whole product field and so do not affect the main brand/private label comparison in any direct manner.

3.7 SUMMARY

Buyer behaviour theory is drawn upon extensively throughout the empirical analyses. Its regularities provide the analytical framework within which observed data are compared with theoretical predictions. Indeed, the model predictions provide the interpretive norms against which we compare our new private label data. Though the models may at first seem abstract, an examination of their assumptions reveals something about the underlying reasons as to why they describe buyer behaviour. This is developed further in the discussion in Chapter 9 where results and interpretation are brought together.

The analysis structure is the same in each of the three empirical chapters. We begin by examining individual brand and private label purchase behaviour, then how people buy from one time period to another, and finally examine how people spread their purchases across the product field. The technique enables us to examine aggregate buying behaviour in a systematic manner by dividing it up into various categories of interest.

The NBD and Dirichlet models are used to provide theoretical predictions. The calculations of the two stochastic models are derived from a computer software package, BUYER (Uncles 1988) in a similar way to the manual calculations shown. This produces both observed and theoretical tabulations in the format required and the software was developed with much input from these analyses.

The models have been shown to successfully describe purchasing behaviour and so provide a sound basis on which to study private labels. The NBD model assumes that each items sales are stationary; the Dirichlet that the market is both stationary and unsegmented. These assumptions have been shown to be largely fulfilled in practice and even when deviations do occur, they do not affect the main brand/private label comparison.

We now move on to using these models in the next four empirical chapters. The first of which shows the models being used to provide a norm against which we compare private label purchasing patterns.

PART 2 - RESULTS

CHAPTER 4 - HOW PEOPLE BUY PRIVATE LABELS

CHAPTER 5 - AN ANALYSIS OF THE HIGH PRIVATE LABEL PURCHASE FREQUENCY

CHAPTER 6 - HOW PEOPLE BUY PRIVATE LABELS WITHIN STORE CHAINS

CHAPTER 7 - HOW PEOPLE BUY PRIVATE LABELS ACROSS TWO PRODUCT FIELDS

CHAPTER 4 : HOW PEOPLE BUY PRIVATE LABELS

4.1 Introduction**4.2 Data Analyses****4.2a Components of the Sales Equation****Penetration****Average Purchase Frequency****The Sales Relationship****Summary****4.2b Period To Period Buying****Repeat Buying****New and Lapsed Buying****Summary****4.2c Item Purchase Frequency Distribution****4.2d Product Field Buying****Total Product Purchase****Share Of Requirements****Sole Buying****Duplicate Buying****Summary****4.3 Summary And Conclusions**

4.1 INTRODUCTION

The objective of this chapter is twofold: to determine whether private labels have the same buying patterns as have already been widely established for branded goods; and to illustrate the analysis techniques used throughout the thesis.

In this chapter, the main results concerning the buying patterns for different brands and private labels are detailed. It is largely an exploratory chapter in which we aim to identify any regularities in private label buying patterns. Once such a framework has been established, we can then start to interpret differences and similarities between brands and private labels. There are two main sections. Section 4.2 reports data analyses and results; section 4.3 summarises these findings in terms of regularities and deviations. Only the basic results are given here with systematic deviations being dealt with in more detail in chapters 5, 6 and 7.

In section 4.2, the components of the sales equation (penetration and purchase frequency) are examined, and the important relationship between them. Then we look at buying items from one period to the next and compare these with NBD model predictions. Next, we examine the purchase frequency distribution for different items, again comparing results with the NBD model. The NBD, rather than the Dirichlet is used because it is easier to obtain repeat buying measures, and results are usually similar from both models under normal circumstances. Finally, buying across the entire product field is examined. The emphasis therefore moves from how people buy individual brands and private labels to how they spread their purchases across the whole product field as was explained in the analysis structure in section 3.3 (page 50).

Throughout, the analysis results are compared across 5 quite different product fields so as to assess the generality of any findings. The observed private label data are compared with theoretical estimates and with brand measures. There is therefore a two-way comparison. This is because if a deviation arose when private label estimates were compared with just the model, it would be unclear whether it was a general product field or private label issue. As the models have been shown to predict brand buying behaviour well, a consistent private label difference in a product field where brands are being bought in line with expectations, is regarded as a deviation.

4.2 DATA ANALYSES

Five product fields are examined in this chapter: Fruit Squash, Liquid Fabric

Conditioner, Baked Beans, Instant Coffee and Washing Up Liquid with data for 48 weeks. However, for reasons of clarity, detailed results are mainly provided for Fruit Squash in London. This is because it has a high share of private labels and so lends itself to detailed analyses. It is also found that people buy Squash brands in much the same way as is expected from theory, which means that it provides a good background against which any differences in private label buying behaviour ought to show up. Other product fields are shown in a more summarised form.

We focus on results which have been generalised across different data sets. Results which are brand or product field specific are noted, but are not examined in detail because they lack reliability and in the thesis we are mainly concerned with general private label issues.

Data are chosen so that results can be compared across different retail situations, time periods and product fields. For example, private label market shares vary considerably depending on the product field and region under consideration. Consequently data are examined in product fields where private label shares vary from 15% to nearly 60% (Table 1.2 page 32); buying patterns in London and Lancashire regions are analysed because they have different retail mixes with Sainsbury strong in London, and KwikSave strong in Lancashire.

All results are compared in two ways. First by showing the patterns of brand buying behaviour which are already well established (Ehrenberg 1972, 1988). Then new private label results are discussed in the light of these patterns. These either have the same buying patterns as brands and as expected from the theory. Alternatively they can differ in some way. The analysis style adopted differs from many statistical methods because rather than being based on a hypothesis testing framework, the aim is to assess both the overall degree of fit and the pattern of discrepancies. The real power of the models lies in their ability to provide theoretical norms, so that terms like "more or less than expected" may be defined using these norms.

Small brands and private labels are aggregated into "Other Brands" (OB), and "Other Private Labels" (OBPL). This is because small sample sizes (20 households or below purchasing in 48 weeks) give results that are greatly influenced by the behaviour of a small number of buyers. Often, their results are quite deviant as is reflected by a comparison with other items and the theoretical estimates. However, the deviations are not consistent and so do not tell us anything about small brands or private

labels. "Item" refers to any brand or private label, and is used as a global term throughout the thesis. This is to prevent confusion between general results and those specific to brands or private labels. All theoretical estimates are shown in parentheses.

We now begin the empirical analyses whereby private label buying patterns are compared with those of branded items.

4.2a Components Of The Sales Equation

In section 3.3a (page 50), the multiplicative sales equation was presented. This shows how aggregate sales can be broken down into 2 main components, penetration b , and average purchase frequency, w . They provide a summarised picture of what constitutes overall sales and so are a good starting point from which to examine how private labels are bought in comparison to brands.

Brand Penetration

The proportion of households buying a specific item at least once in a given time period, the penetration of that item, is denoted as b_x for item x .

Research has shown that consistent patterns of brand buyer behaviour exist at the aggregate level (Ehrenberg 1972, 1988). For example, as the analysis period lengthens, the value of b_x increases less than pro-rata to time. This growth in penetration can be closely predicted by the Dirichlet model. Furthermore, penetration is higher for items with larger market shares and so varies within a given time period. In Table 4.1 we determine whether private labels follow these same patterns.

All tables are ordered by penetration with larger items at the top of each group. Some item names are abbreviated; these are OB, for Other Brands; RB, for Robinsons Barley; and OBPL for Other Private Labels (Table 4.1).

**Table 4.1 : Observed And Theoretical Penetration For Fruit Squash (London)
(bx)**

weeks	4		8		12		24		48	
	O	T	O	T	O	T	O	T	O	T
Any	32	(31)	43	(43)	54	(55)	61	(61)	72	(70)
Brands										
Robinsons	7	(7)	10	(10)	16	(15)	19	(18)	29	(24)
OB	4	(4)	6	(6)	11	(9)	14	(11)	22	(15)
Quosh	4	(4)	7	(7)	10	(10)	13	(13)	20	(18)
Kia	3	(3)	5	(4)	7	(6)	10	(8)	15	(11)
RB	2	(2)	4	(3)	5	(5)	7	(7)	10	(9)
Corona	1	(1)	1	(1)	1	(2)	2	(3)	3	(4)
Average	4	(4)	6	(6)	8	(8)	11	(10)	17	(14)
Private Labels										
Sainsbury	10	(11)	14	(17)	20	(24)	23	(29)	30	(38)
OBPL	6	(7)	10	(10)	16	(15)	20	(19)	29	(25)
Tesco	3	(4)	4	(6)	6	(9)	8	(11)	11	(15)
Coop	2	(2)	3	(4)	4	(6)	6	(8)	8	(10)
Average	5	(6)	8	(9)	12	(14)	14	(17)	20	(22)

Note : average 24 week base used in fitting the Dirichlet model; O - observed measures, T - theoretical estimates.

Fruit Squash purchasing follows the basic patterns outlined in the previous paragraph. This is important because we can then compare private labels and brands in the knowledge that the product field is bought much in line with the theory. Growth in penetration is closely predicted by the Dirichlet model and levels off in periods of longer duration as saturation is approached; it is observed that 32% (31%) of the population bought any Fruit Squash at least once in a 4 week period and this rises to 72% (70%) in 48 weeks. Items with larger market shares have a higher penetration than smaller ones; Robinsons, with a market share of 15% is bought by 29% of buyers in 48 weeks as compared to 3% buying Corona with only a 1% share.

Private labels also largely follow these patterns. Their penetration varies within a time period and does so roughly in line with model predictions. Average private label penetration rises from 5% (6%) to 20% (22%) in 4 to 48 weeks. Large private labels have a higher penetration than do smaller ones.

However, private labels tend to be slightly over-predicted by the model. In 48 weeks the average private label is bought by 20% of buyers as compared to (22%) predicted. This occurs for each private label except the OBPL grouping. (OBPL and Corona are consistently deviant and are discussed in note 1 page x, and then in more detail in section 5.4b).

Therefore, private labels largely follow the same basic penetration patterns as brands, and as we expect from our theory. However, there is a tendency for private label penetration to be lower than expected when fitting one overall model (excluding OBPL), and for brands (excluding Corona) to have slightly higher penetration levels. This is a finding which also occurs on average for our other five product fields (as shown later in Table 4.3 page 89).

Average Purchase Frequency

The remaining component of the sales equation, the average number of purchases made by households in a given period, the average purchase frequency, is denoted by w_x for item x .

Average purchase frequency tends to grow less than pro-rata to time, and can be closely predicted by the Dirichlet model. Purchase frequency also tends to be higher for larger items, but varies much less between items in a given time period than does penetration. This means that larger items are bought more often than smaller ones (Table 4.2).

Table 4.2 : Observed And Theoretical Average Purchase Frequency For Fruit Squash (London) (wx)

weeks	4		8		12		24		48	
	O	T	O	T	O	T	O	T	O	T
Any	2.0	(2.0)	2.9	(2.9)	4.6	(4.6)	6.2	(6.2)	10.5	(10.8)
Brands										
Robinsons	1.4	(1.4)	1.8	(1.8)	2.3	(2.4)	2.8	(3.1)	3.8	(4.5)
OB	1.4	(1.4)	1.6	(1.7)	1.9	(2.3)	2.2	(2.8)	2.8	(4.1)
Quosh	1.4	(1.4)	1.8	(1.8)	2.3	(2.3)	2.8	(2.9)	3.7	(4.2)
Kia Ora	1.4	(1.4)	1.6	(1.8)	2.0	(2.3)	2.2	(2.9)	2.8	(4.2)
RB	1.3	(1.4)	1.6	(1.7)	2.1	(2.2)	2.5	(2.7)	3.3	(3.9)
Corona	1.9	(1.4)	2.4	(1.7)	3.2	(2.2)	3.4	(2.6)	4.0	(3.7)
Average	1.5	(1.4)	1.8	(1.7)	2.3	(2.3)	2.7	(2.8)	3.4	(4.1)
Private Labels										
Sainsbury	1.7	(1.5)	2.3	(2.0)	3.3	(2.7)	4.3	(3.4)	6.6	(5.3)
OBPL	1.5	(1.5)	1.9	(1.8)	2.4	(2.5)	2.8	(3.0)	3.9	(4.5)
Tesco	1.8	(1.4)	2.3	(1.7)	3.3	(2.3)	3.9	(2.8)	5.4	(4.1)
Coop	1.7	(1.4)	2.3	(1.7)	3.1	(2.2)	3.6	(2.7)	5.2	(3.9)
Average	1.7	(1.5)	2.2	(1.8)	3.0	(2.4)	3.7	(3.0)	5.3	(4.5)

Note : average 24 week base used in fitting the Dirichlet model.

We find that on the whole Fruit Squash purchasing follows these patterns. Growth in average purchase frequency is less than pro-rata to time; in 4 weeks any Fruit Squash is bought twice and this rises to over 10 times in 48 weeks, with most of the rise being in the first 24 weeks. The usual downward trend within the body of the table whereby larger items are bought more often than smaller ones is not clear, especially for brands. However this does not generalise to other product fields.

Private labels follow some of the patterns outlined above. Growth in their purchase frequency is less than pro-rata to time; some 56% of the average private label growth from 4 to 48 weeks being in the first 24 weeks. Their purchase frequency within the same time period falls, though less than pro-rata with penetration (excluding OBPL). For example, in 48 weeks, the larger Sainsbury private label is bought more often than the smaller Tesco private label. Sainsbury with a market share of 26% is purchased 6.6 times compared to Tesco with an 8% share being bought 5.4 times.

However, private labels (excluding OBPL) differ from the model predictions and brand patterns in one way. Their purchase frequency is consistently underestimated by the model. In 48 weeks the average private label is bought 5.3 times as compared to a theoretical (4.5) times. After allowing for market shares, which is essentially what the model does, private labels have a higher purchase frequency than their branded counterparts and than is predicted.

These results occur on average across the other product fields examined (Table 4.3). Though private labels follow the fundamental patterns they tend to have a lower penetration and higher purchase rate than either the average brand or than the predicted figure. In 48 weeks the average private label is bought by 8% (9%) of buyers 6.3 (5.4) times. The corollary is that the average brand has slightly more buyers who buy less often than is predicted. (OBPL is excluded from the average private label rate because it is consistently below the model predictions. See note 1 page x). On average private label buying rates are nearly 20% higher than predicted and their penetration over 10% below. The opposite occurs for brands.

Table 4.3 : Penetration And Average Purchase Frequency For The Average Brand And Private Label For 5 Product Fields And Two Regions (48 weeks)

Product Field	Region	Average Brand				Average Private Label			
		b		w		b		w	
		O	T	O	T	O	T	O	T
Fruit Squash	Lon	17	(14)	3.4	(4.1)	16	(21)	5.7	(4.4)
	Lan	25	(24)	4.3	(4.5)	6	(7)	5.1	(3.8)
Fab. Cond	Lon	18	(15)	3.0	(3.5)	11	(12)	3.7	(3.3)
	Lan	22	(21)	3.6	(4.0)	4	(5)	3.6	(3.4)
Beans	Lon	14	(12)	7.8	(10.4)	11	(12)	17.5	(11.5)
	Lan	20	(19)	9.7	(11.4)	6	(5)	7.6	(9.8)
Coffee	Lon	10	(8)	3.8	(4.5)	9	(10)	5.6	(4.8)
	Lan	10	(9)	4.5	(5.2)	7	(7)	5.1	(4.9)
Washg.Liquid	Lon	15	(14)	3.3	(3.8)	5	(6)	4.4	(3.6)
	Lan	17	(17)	4.3	(4.5)	3	(4)	4.4	(4.1)
Average		17	(15)	4.8	(5.6)	8	(9)	6.3	(5.4)

Note : average 24 week base used in fitting the Dirichlet model.

There is only one discrepancy out of 10 samples. For Baked Beans (Lancashire) the private label purchase rate is lower than predicted and this is also the case for brands. There is no obvious explanation for this, especially as the same patterns fails to occur for Baked Beans in London.

There is much variation in the discrepancies in Table 4.3 and two important points are discussed below.

First, the nature of the Dirichlet model is such that an over-prediction in b will result in an under-prediction in w . This is because their product (ie sales) is used as input into the model. We might therefore expect that a 10% higher w would be compensated for by a 10% lower b . This is in fact what we find. On average the private label w is 17% higher than predicted and its penetration is 14% below (Table 4.4). For brands, the deviations for b and w are similar at 11% and 13% respectively. The slightly higher w deviation for private labels is largely a London effect; private label purchase rates in London are 22% higher than predicted as compared to 13% in Lancashire. Differences between individual stores private labels are discussed in chapter 6.

Table 4.4 Average Absolute Percent Deviation Between Observed And Theoretical Figures In Table 4.3

Region	Brand		PL		Average
	b	w	b	w	
London	17	17	13	22	17
Lancashire	5	8	15	13	11
Average	11	13	14	17	

Note : Baked Beans (Lancashire) deviation is not included in the private labels average as this did not follow the same patterns as other private labels.

Secondly, on average deviations are larger in London than Lancashire, 17% and 11% respectively. This is largely the result of a much closer fit in Lancashire, 5% and 8% for b and w respectively. This could be a result of the low share of

the market which is accounted for by private labels in that region. Private label variation is mostly similar in both regions with the exception of the high private label w in London.

An important finding is that the way in which private labels are bought in respect of b and w appears to differ from that for brands. On average private labels are bought more often, by fewer people, than either brands in general or the predicted values. This result occurs on average across most of the product fields examined, despite their variations in private label market shares and differing retail mixes (Note 1 page 100).

The difference is discussed and largely accounted for in Chapter 5. However, first we need to establish its robustness and explore it in more detail to help understand where it shows through and why. The product of penetration and purchase frequency is sales, and we now examine the repercussions of the above result on the sales equation.

The Sales Relationship

The multiplicative sales equation shown in section 3.3 considers b and w as the main components of the sales of a particular item. Higher sales could come from more buyers (a higher penetration) and/or from them buying more often (higher average purchase frequency). The fact we have found that the values of the components of the sales equation differ for brands and private labels needs further investigation.

We examine the sales relationship using a simple model [$w(1-b)$]. w tends to decrease as b falls so that the expression [$w(1-b)$], where b is expressed as a proportion, is theoretically constant within a product field. This is a good way of focussing on the private label deviation because the equation concentrates specifically on b and w without the added complexities of the Dirichlet. There is usually only one combination of b and w for each item in a product field. So a brand with higher penetration will have a slightly higher purchase frequency than a brand with a smaller penetration (Table 4.5). This important sub-pattern is referred to as Double Jeopardy and was first noted by McPhee (1963). It has since been found to exist in many product fields (Ehrenberg, Goodhardt and Barwise 1988). As a consequence of the Double Jeopardy pattern, w can only be deemed high or low with reference to b and vice versa.

Table 4.5 : The Relationship Between Observed Penetration And Average Purchase Frequency For Fruit Squash (London 48 weeks)

Brands	Market Share	b	w	w (1-b)
Brands				
Robinsons	15	29	3.8	2.7
OB	8	22	2.8	2.2
Quosh	10	20	3.7	2.9
Kia-Ora	6	15	2.8	2.4
RB	5	10	3.3	2.9
Corona	1	3	4.0	3.9
Average	8	17	3.4	2.8
Private Labels				
Sainsbury	26	30	6.6	4.6
OBPL	15	29	3.9	3.2
Tesco	8	11	5.4	4.8
Coop	6	8	5.2	4.8
Average	14	20	5.3	4.4

However, the relationship [$w(1-b)$], is not constant within the product field. Indeed for Fruit Squash (London), the expression for the average private label is over 50% higher than for the average brand, 2.8 and 4.4 respectively. This reinforces the previous result whereby private labels have a high purchase frequency in relation to their penetration and to brands. Though the Double Jeopardy pattern does not exist within the product field, it does within the private label and brand groups (OBPL and Corona excepting).

Note 1 : OBPL and Corona

These two items do not follow the patterns identified above. Indeed OBPL are bought much like any brand, and Corona much like a private label. This occurs because of differences in their distributions. The fact that they are deviant in this way supports the explanation for the discrepancy which is discussed in Chapter 5. Their deviant nature does not therefore reduce the generalisability of results in this chapter.

The private label deviation is examined further using the simple quantitative model $[w_o / (1-b)]$ where w_o is the average $w(1-b)$ for a selection of items. This was developed to describe the sales relationship (Ehrenberg 1972, 1988 Chapter 11) and to provide theoretical estimates of w once having allowed for b . It should be true as long as the rate of product field buying is similar for different brands, and buying of one brand is independent of another. These two assumptions have been empirically tested and both are commonly found to be approximately true in practice (as shown in section 4.2d).

We use this model here for two reasons:

First, to measure the size of the private label deviation by comparing private label buying rates with theoretical estimates based on the average $w(1-b)$ for brands only. w_o is therefore set at 2.8 from Table 4.5. All other theoretical predictions are based on the model fitted to the whole product field rather than to brands only as we do here. In this case the predicted average private label w is (3.5) which is more than 50% lower than the observed w of 5.3. This means that if the private label were bought as through it were a brand, its w would be 50% lower than is observed. It is also interesting to note that for the brand only model, the OBPL result is the same as predicted.

Secondly, to provide another theoretical estimate rather than relying solely on Dirichlet predictions. The $[w_o / (1-b)]$ model enables us to focus on the relationship between b and w without some of the complexities of the Dirichlet model. In this case $w_o = 3.4$, which is the product field average $w(1-b)$ from Table 4.5. We find the observed figures differ from the theoretical predictions; the average private label w is higher than predicted 5.3 (4.3), whereas the average brand w is lower 3.4 (4.1). This reinforces the previous Dirichlet estimates (Table 4.3) that the rate of buying by private labels buyers is higher than is predicted from theory. Furthermore, that according to theory, rates of buying by brand and private label buyers should be more or less equal once allowance has been made for differences in market share.

Table 4.6 : Observed And Theoretical [wo / (1-b)] Rates Of Buying For Fruit Squash (London 48 weeks)

Brands	O	T wo=2.8	T w=3.4
Brands			
Robinsons	3.8	(3.9)	(4.8)
OB	2.8	(3.6)	(4.4)
Quosh	3.7	(3.5)	(4.3)
Kia-Ora	2.8	(3.3)	(4.0)
RB	3.3	(3.1)	(3.8)
Corona	4.0	(3.0)	(3.5)
Average	3.4	(3.4)	(4.1)
Private Labels			
Sainsbury	6.6	(4.0)	(4.9)
OBPL	3.9	(3.9)	(4.8)
Tesco	5.4	(3.1)	(3.9)
Coop	5.2	(3.0)	(3.7)
Average	5.3	(3.5)	(4.3)

That private labels have a higher purchase frequency than predicted and a lower penetration is a robust result. So far we have shown that it occurs in five product fields and two regions.

It also occurs in data from some market reports from the late 1960's and early 1970's (Aske Research 1969, 1970). Theoretical Dirichlet predictions were obtained from the observed data. It was found that private labels have a higher purchase frequency than expected 4.8 (3.7), and a slightly lower penetration 9% (11%) (Table 4.7). Brands are more closely predicted with 23% (23%) buying 4.1 (4.2) times.

Table 4.7 : Penetration And Average Purchase Frequency For 1969 - 1970 (48 weeks)

Brands	b		w		Private Labels				
	O	T	O	T	O	T	O	T	
Soup	41	(39)	7.0	(7.3)	Soup	17	(20)	6.7	(5.9)
Spaghetti	30	(30)	4.1	(4.1)	P.Milk	10	(15)	4.7	(2.8)
Fish	28	(26)	4.3	(4.6)	Spaghetti	10	(12)	4.4	(3.7)
P.Milk	16	(14)	2.3	(2.8)	Margarine	9	(9)	3.9	(3.7)
Margarine	18	(18)	4.0	(4.0)	Fish	8	(10)	5.4	(3.7)
Dentifrice	17	(17)	3.2	(3.2)	Dentifrice	5	(6)	3.5	(2.9)
Food Drink	14	(14)	3.8	(3.7)	Food Drink	5	(7)	4.9	(3.5)
Average	23	(23)	4.1	(4.2)		9	(11)	4.8	(3.7)

Key : P.Milk - powdered milk.

Note: Figures represent the average of all brands and private labels in the product field studied. The averages are ordered by penetration.

Summary

The values of the components of the sales equation differ for the average brand and private label. Given a brand and private label with the same market share, the private label will have a higher purchase frequency than the brand, a slightly lower penetration, and this is reinforced by the theoretical predictions.

Furthermore, this new finding is not specific to Fruit Squash in London. It is robust and exists on average across 5 quite different product fields; in both London and Lancashire; for Automatic Washing Powder and Tea Bags, which have been tested using private data sources; and also in data from the late 1960's and early 1970's in a very different retail environment. This fundamental discrepancy is discussed in detail and largely accounted for in chapter 5.

So far we have examined the summary measures of buyer behaviour and found that fewer people buy private labels more frequently than is predicted from theory and vice-versa for brands. This difference has repercussions on other measures of buyer behaviour as shown in the following sections. However, though it is difficult to isolate these repercussions from any other private label deviations, the analyses are still shown because we need to know more

about the high private label purchase rate so as to be able to explain its occurrence. In the following sections we determine whether this difference is general (ie occurs systematically throughout the population of buyers), or whether it is peculiar to a certain group of buyers such as sole buyers.

In section 4.2b which follows, we examine how people buy private labels from one time period to another. Analyses of repeat buying are for two 24 week time periods. The NBD rather than the Dirichlet is used because it is simpler to use, and results are usually similar from both models anyway under normal circumstances.

However, there is one difference between the two models which requires some explanation because of its importance in interpreting the deviations. The NBD uses penetration and average purchase frequency for each item directly as input whereas the Dirichlet uses their product which is market share. This particular difference means that in using the NBD, we are essentially allowing for the high private label purchase frequency because this is input in the base period. Therefore, a close fit does not mean that the high private label purchase rate does not exist, rather that there are no other differences between brands and private labels once having allowed for the high purchase rate. If the Dirichlet were used, the private label purchase rate would show up as a higher incidence and slightly higher rate of repeat buying.

However, there were some problems with the NBD model which have limited our repeat buying analyses in this chapter. The model tends to significantly over-predict the incidence and slightly under-predict the rate of repeat buying. This also occurred in the other product fields any cannot yet be explained. Because of such problems, it is difficult to separate product field and private label results. So in this Chapter repeat buying analyses are limited to assessing the repercussions of the high private label purchase rate. More detailed repeat buying analyses are undertaken in chapter 6 after having allowed for the private label discrepancy. Therefore, Chapter 6 results provide the main results for private label repeat buying behaviour.

Average purchase frequency is directly related to the incidence of repeat buying. So the high private label purchase rate will have repercussions on repeat buying which we now consider.

4.2b Period To Period Buying

There are three components of repeat buying which together provide a picture of buying in the aggregate: repeat, new and lapsed buying. In a stationary market, sales are stable from one period to the next period of equal length. However within this, there is still change at the individual level as some people buy in just one of two periods, whilst others buy in both. Those who buy in both periods are repeat buyers. Those who only buy in the second are new buyers. Those who only buy in the first of two periods are lapsed buyers. In stationary market conditions, the numbers of new and lapsed buyers are the same.

Repeat Buying

The incidence and rate of repeat buying are examined first, followed by the same for new and lapsed buying.

Incidence of Repeat Buying

The proportion of item x buyers in the first period who also bought it again in the second period is denoted by br_x . Values of br_x are usually similar within a product field from one period to the next of equal length. There is usually a slight relationship with penetration in that large items generally have more repeat buyers than smaller ones, another reflection of Double Jeopardy.

We find that patterns of repeat buying for private label Fruit Squash are similar to those found for brands. The incidence of repeat buying varies little between items in the same time period. For example br_x varies from 54% to 69% (excluding Corona), despite market shares varying from 6% to 26%. The Double Jeopardy pattern is unclear in this table, but this is for brands and private labels alike. The Coop private label has a particularly high incidence of repeat buying in comparison with other private labels, but this is unusual and does not generalise further (Table 4.8).

**Table 4.8 : Observed And Theoretical Incidence
Of Repeat Buying For Fruit Squash (London
(br) 24 weeks)**

weeks	O	24 T	
Any	86	(86)	
Brands			
Robinsons	53	(69)	
OB	49	(62)	
Quosh	62	(68)	
Kia-Ora	51	(61)	
RB	49	(65)	
Corona	27	(70)	
Average	49	(66)	Average Excluding Corona 53 (65)
Private Labels			
Sainsbury	68	(76)	
OBPL	57	(69)	
Tesco	54	(73)	
Coop	69	(72)	
Average	62	(72)	

Note : average 24 week base used in fitting the NBD model.

The discrepancy across the product field between the observed and theoretical incidences of repeat buying makes the interpretation of results more difficult. The model over-predicts the incidences by some 20% to 30%.

However, on average the incidence of private label repeat buying is more closely predicted by the model than is the average brand - a 10 and 17 point difference respectively (Table 4.8). This larger brand difference is mainly due to Corona. When excluded, the average brand figures change to 53% (65%), a 12 point difference which is more in line with the private label difference. Brands and private labels are therefore similarly over-predicted by the model.

In this case private labels are predicted to have a slightly higher incidence of repeat buying than brands (72%) and (66%) respectively. This is a result of

their high average purchase frequency identified earlier and because they have a higher market share than the average brand.

The incidence of repeat buying for private labels is similar to that for brands. The NBD over-predicts all items in periods of 24 weeks. The fact that the theoretical predictions are almost equal means that once the high private label purchase frequency and market share differences are taken into consideration, there are no other differences between the incidence of repeat buying for brands and private labels.

Buying Frequency of Repeat Buyers

The incidence of repeat buying provides one dimension of repeat buying behaviour. Another aspect to consider is the average rate of buying by these buyers. The purchase frequency of repeat buyers is denoted as w_{rx} for item x . The high private label purchase frequency should be reflected in a slightly higher repeat buying rate.

As with earlier measures of buying behaviour, there are some well-established patterns for rates of repeat buying. Usually these rates are fairly constant for items in the same time period. There is a slight tendency for larger items to attract a higher rate of buying by repeat buyers than smaller ones, which is another reflection of Double Jeopardy (Ehrenberg 1972, 1988).

Private label repeat buyers tend to follow these patterns (Table 4.9). When Corona is excluded from the brand average, values of w_{rx} vary from 2.7 to 5.4. The Double Jeopardy pattern is unclear in this table, even allowing for Corona and OBPL which distort the pattern.

Table 4.9 : Observed And Theoretical Purchase Frequency of Repeat Buyers For Fruit Squash (London (wr) 24 weeks)

	O	T	
Any	7.2	(7.0)	
Brands			
Robinsons	4.0	(3.4)	
OB	2.7	(2.8)	
Quosh	3.9	(3.4)	
Kia-Ora	2.6	(2.7)	
RB	2.7	(3.1)	
Corona	8.5	(4.3)	
Average	4.1	(3.3)	Excluding Corona 3.2 (3.1)
Private Labels			
Sainsbury	5.2	(5.2)	
OBPL	3.6	(3.5)	
Tesco	5.4	(4.8)	
Coop	5.2	(4.5)	
Average	4.9	(4.5)	

Note : average 24 week base used in fitting the NBD model.

There is again a discrepancy between the observed and theoretical predictions. Given that private labels have a high purchase rate, this should be reflected in a slightly higher observed wr. This is in fact what we find. Private label repeat buyers make an average of 4.9 (4.5) purchases in 24 weeks. Their rates are consistently higher than predicted. Brand rates are also much higher than predicted, 4.1 (3.3) but this is mainly due to Corona. The fit is much closer when Corona is excluded, 3.2 (3.1).

Therefore, private label repeat buying patterns are similar to those for brands. The high private label purchase frequency manifests itself in there being more repeat buyers who buy slightly more often than is observed for brands. If we assume that the model deviation is similar in nature for brands and private labels; the incidence of repeat buying is closely predicted for brands and private labels, but the latter are bought slightly more often.

Not everyone buys in both time periods. There are also those who are new buyers to the analysis period whose purchase behaviour we have not yet examined. We examine new and lapsed buyers next, but not in great detail because they are simply the complement to repeat buyers.

New and Lapsed Buying

The term "new" does not necessarily mean this is the first purchase, as they may have bought months ago and are now re-entering the market. "New" means new to the second period under consideration, and this will include both first time buyers and re-entrants.

Incidence of New and Lapsed Buying

The penetration of new and lapsed buyers is denoted as b_{nx} and b_{lx} for item x . Their average purchase frequencies are w_{nx} and w_{lx} .

Under stationary conditions, the number of buyers in each period of equal length is expected to be the same. Therefore, the proportion of new buyers (those coming into the market), should be equal to the proportion of lapsed buyers (those leaving the market). Lapsed buyers represent the difference between all buyers and repeat buyers. The incidence of new and lapsed buying is the complement to that for repeat buying. For example, it was observed in Table 4.8 that 86% of buyers were repeat buyers. This means that 14% failed to repeat buy and are new buyers to the analysis period. Together, repeat and new buyers comprise all buyers.

There are some well-established patterns of new and lapsed buying behaviour. Typically, the incidence of new and lapsed buying varies little between items in the same period. Larger items tend to have fewer new buyers because most of their customers are repeat buyers. New and lapsed buyers tend to be light buyers, with a virtually constant rate of buying of approximately 1.4 times in 48 weeks. This is one reason why larger items tend to have a higher overall purchase frequency as more of their customers are repeat buyers.

On the whole private labels follow these patterns. The incidence of new and lapsed buying varies from 31% to 51% (excluding Corona Table 4.10), despite market shares of 6% to 26%. However, the Double Jeopardy pattern is not clear in this data set and this is so for brands and private labels alike. When the high rates of new and lapsed buying for RB and Corona are excluded, rates

vary from 1.6 to 1.8, in line with what is usually found.

Model predictions suffer from the same problems as were found for repeat buying. However, new and lapsed buying is covered in more detail in chapter 6. For the moment, we identify the repercussions of the high private label purchase rate. Private labels have fewer new and lapsed buyers than brands, 38% and 51% respectively, which is a direct result of the high private label w. Buying rates are slightly higher than predicted, but this is so for brands and private labels.

Table 4.10 : Observed And Theoretical Incidence And Rate Of New and Lapsed Buying For Fruit Squash (London 24 weeks)

	bn,bl		wn,wl	
	O	T	O	T
Brands				
Robinsons	47	(31)	1.8	(1.4)
OB	51	(38)	1.8	(1.4)
Quosh	38	(32)	1.6	(1.4)
Kia-Ora	49	(39)	1.7	(1.4)
RB	51	(35)	2.5	(1.4)
Corona	73	(30)	1.0	(1.4)
Average	51	(34)	1.7	(1.4)
				Average Excluding Corona
				47 (35)
Private Labels				
Sainsbury	32	(24)	1.8	(1.5)
OBPL	43	(31)	1.7	(1.4)
Tesco	46	(27)	1.8	(1.4)
Coop	31	(28)	1.7	(1.4)
Average	38	(28)	1.8	(1.4)

Note : average 24 week base used in fitting the NBD model.

Therefore, the high private label purchase rate shows through as a lower incidence of new and lapsed buying than for brands and a slightly higher purchase rate. Apart from this there are no other apparent differences in buying patterns between brands and private labels. Though these results are only shown for Fruit Squash (London), the observed findings are similar in the other four product fields.

Summary

The fact the NBD model predictions are poor for the whole product field limits their usefulness. It is difficult to separate a product field deviation from any other deviation under these conditions. However it seems that the model over-predicts the incidence of repeat buying by approximately a third, and under-predicts the rate of repeat buying, but to a lesser degree.

The reasons for this discrepancy are not known at present. It has not shown up in previous research because it is related to the specific method used to generate NBD predictions. The method used in this Chapter differs slightly from that used in previous research (see Chapter 9 for more explanation). The deviation, though interesting, is not examined in detail because it is outside the scope of the thesis and as it affects brands and private labels similarly, it does not affect the main brand/private label comparison except in making it more difficult.

The observed results can be interpreted though. The high private label w shows through as a higher incidence of repeat buying than brands, 62% and 53% respectively; and a slightly higher rate of repeat buying, 4.8 and 4.3 times. The corollary being that there are fewer new and lapsed buyers with a similar rate of buying to brands. Given that w is essentially a measure of buying incidence, this makes sense. Intuitively, a higher w should be reflected in a higher incidence of repeat buying. Because of the Double Jeopardy relationship, a higher incidence of buying is accompanied by a higher rate of buying, which is what we find.

Apart from these manifestations of the high private label w , there seem to be no additional differences between brands and private labels. If there were, they would show through as a deviation from the NBD model which differed for brands and private labels. So private labels do not seem to attract more repeat buying loyalty for example, than any other brand, despite being unique to one store. Repeat buying patterns are similar for both.

So far we have examined w as a population average and found that private label buyers have a higher rate of buying than brand buyers, *ceteris paribus*. This has repercussions on repeat buying patterns as explained above, but no other differences have been identified.

However, even among private label buyers, individuals differ in their rate of buying. This means that the private label purchase frequency deviation may vary across the buying population. We now examine the distribution of purchase frequencies in order to identify whether there are any further differences between brands and private labels, and to examine any repercussions of the high w . By continuing to explore how the high private label purchase frequency affects other measures of buying behaviour, this helps with our interpretation in chapter 5.

4.2c Item Purchase Frequency Distribution

The distribution of brand and private label purchases shows how often buyers purchase in a given time period. The shape of the distribution is fundamental to how well the model fits the data. Generally the distribution displays a common shape, a downward sloping positively skewed curve which can be predicted by the NBD and Dirichlet models. We continue to use the NBD model because a close fit means that the only difference between brands and private labels is that relating to the high private label purchase frequency. Once this is taken into consideration, private labels are bought in the same way as brands and as is expected from theory. The NBD application therefore provides another means of testing this result.

What we tend to find with fast moving consumer goods is that few people are heavy buyers of an item, the majority being light buyers who may only make one purchase of a particular item in 48 weeks. Also, that larger items have more heavy buyers (and fewer lighter buyers) than smaller items (Ehrenberg 1972, 1988).

Private labels follow these same buying patterns (Table 4.11). On average 52% of brand and 36% of private label buyers bought any Fruit Squash once in 48 weeks, 16% and 18% purchased twice and 7% and 9% did so three times. Both brands and private labels have similar positively skewed purchase frequency distributions, mostly light buyers, with a few heavy buyers. Larger private labels have more heavy buyers (those making 6 or more purchases) and fewer light buyers (those buying once or twice) than a smaller private label. For example, the Sainsbury private label only has 28% buying once which is lower than the smaller private labels which have over 38% of once only buyers.

Table 4.11 : Frequency Distribution Of Item Purchase For Fruit Squash (London 48 weeks)

	Number Of Purchases											
	1		2		3		4		5		6+	
	O	T	O	T	O	T	O	T	O	T	O	T
Any	33	(32)	16	(17)	10	(10)	7	(7)	5	(5)	29	(29)
Brands												
Robinsons	42	(36)	19	(18)	7	(11)	6	(8)	4	(6)	22	(21)
OB	51	(44)	19	(20)	9	(12)	6	(7)	4	(5)	11	(12)
Quosh	47	(38)	17	(18)	7	(11)	6	(8)	5	(5)	18	(20)
Kia-Ora	51	(45)	20	(20)	9	(11)	7	(7)	2	(5)	11	(12)
RB	43	(41)	19	(19)	10	(11)	7	(7)	3	(5)	20	(17)
Corona	77	(38)	0	(18)	0	(10)	0	(7)	14	(5)	9	(22)
Average	52	(40)	16	(19)	7	(11)	5	(7)	5	(5)	15	(18)
Private Labels												
Sainsbury	28	(28)	15	(15)	8	(10)	8	(7)	7	(6)	34	(34)
OBPL	38	(36)	24	(18)	7	(11)	7	(8)	4	(6)	20	(21)
Tesco	40	(33)	11	(16)	11	(10)	6	(7)	6	(5)	26	(29)
Coop	39	(34)	22	(16)	10	(10)	2	(7)	2	(5)	25	(28)
Average	36	(33)	18	(16)	9	(10)	6	(7)	5	(6)	26	(28)

Note : average 24 week base used in fitting the NBD model.

Private labels have a slight discrepancy at each end of their distribution. There are more light buyers than predicted 36% (33%) and slightly fewer heavy buyers 26% (28%), and this is similar to the brand purchase frequency distribution (excluding Corona). This is largely a result of non-stationarity which is discussed in Chapter 8.

The fit of the model is also close across all 5 product fields on average (Table 4.12). However, there are more light buyers and fewer medium and heavy buyers than predicted for both brands and private labels, except Baked Beans which are more skewed towards heavy buyers than predicted. Also Fabric Conditioner (London) and Washing Up Liquid (London) private labels are closely predicted by the model.

However, overall the evidence suggests that even before differences in purchase frequencies have been taken into account, private labels have a similar purchase frequency distribution to brands. The private label w does not show through in the purchase frequency distribution because it is already built into the NBD model. However, the fact the model predictions are alike suggests there are no other differences between them once the w has been taken into account.

Table 4.12 : Frequency Distribution Of Item Purchase For The Average Brand And Private Label For Five Product Fields (London and Lancashire 48 weeks)

Number of Purchases												
Product Field	Brands						Private Labels					
	1		2-5		6+		1		2-5		6+	
	O	T	O	T	O	T	O	T	O	T	O	T
Squash	52	(40)	33	(42)	15	(18)	36	(33)	38	(39)	26	(28)
	41	(35)	36	(41)	23	(23)	47	(38)	34	(42)	19	(20)
Fab. Cond	55	(46)	30	(30)	15	(24)	48	(49)	44	(44)	8	(7)
	52	(43)	34	(34)	14	(14)	51	(48)	37	(40)	12	(12)
Beans	24	(28)	31	(34)	45	(38)	24	(25)	31	(31)	45	(44)
	24	(25)	31	(33)	45	(42)	27	(30)	33	(34)	40	(36)
Coffee	43	(35)	28	(39)	29	(26)	47	(37)	34	(40)	19	(23)
	46	(36)	33	(39)	21	(25)	45	(34)	27	(39)	28	(27)
Washg.	47	(41)	39	(43)	14	(16)	43	(43)	40	(39)	17	(18)
	41	(35)	40	(41)	19	(24)	48	(42)	35	(39)	17	(19)
Average	42	(36)	34	(38)	24	(25)	42	(38)	36	(39)	23	(24)

Note : average 24 week base used in fitting the NBD model; first row of each product field is London, second row is Lancashire.

Private labels have a similar positively skewed purchase frequency distribution to brands. Both are closely predicted by the NBD model with a slight surplus of light buyers and a shortfall of medium and heavy buyers on average. The fit of the model reinforces the point that once differences in w are taken into account, private labels are bought just like branded items. Apart from the

private label w, which affects light and heavy buyers alike, there are no other differences in the purchase frequency distributions for brands and private labels.

So far we have examined how people buy one item at a time and how they do this over time. The main difference between private labels and brands is that the former have a higher purchase frequency and slightly lower penetration than is predicted, and than the average brand. This affects the incidence and rate of repeat buying but does not show through in the purchase frequency distribution because the high purchase rate is distributed between light and heavy buyers.

The majority of people have a repertoire of items from which they choose. Given that private labels are often attributed with attracting more loyalty than brands, we now examine whether such differences exist by an analysis of product field purchase behaviour. We also identify any further repercussions from the high private label w.

4.2d Product Field Buying

This section consists of 3 main parts; total product purchasing, sole buying and multi-item buying. Together these provide a detailed picture of which items are bought and how often, how many buyers are 100% loyal, and how many switch between different items.

The Dirichlet model is used here because the NBD caters for one item at a time. The Dirichlet is a product field model which enables us to examine how people spread their purchases across the product field and in what proportions. This means that repercussions of the high w will show through as a model deviation because they are not directly "built" into the model.

Total Product Purchase

The total average product purchase frequency is denoted by w_x for buyers of item x.

Some well-established patterns of buying behaviour have been found to occur in product field buying. Usually, in short time periods of say a week most people buy the product once (Ehrenberg 1972, 1988). Over longer time periods such as a year, there is more opportunity for buyers to buy more of the

product field, and this is what tends to happen. wpx tends to be more or less constant within a product field in the same length time period. There is however a slight relationship with penetration in that buyers of larger items have smaller wpx values. This occurs because more popular items tend to be bought by lighter product field buyers, which is why they are more popular in the first place. Small (less popular) items, on the other hand, are bought by the heavier product field buyers with wider repertoires.

Private label buying follows these patterns (Table 4.13). Private labels attract similar product field purchase patterns as brands. Product field buying rates vary little within the same time period, from 14 to 17 times in 48 weeks as compared to from 15 to 17 times for brands. So private label buyers are not particularly heavy buyers of the product field. Private labels with small market shares tend to have a higher product purchase rate than buyers of larger ones. In this case though, the Tesco and Coop private label are a little out of line, but this is not a consistent finding.

Table 4.13 : Observed Average Total Product Purchase Rates For Fruit Squash (London) (wp)

weeks	4		8		12		24		48	
	O	T	O	T	O	T	O	T	O	T
Any	2	(2)	3	(3)	5	(5)	6	(6)	11	(11)
Brands										
Robinsons	2	(2)	4	(4)	6	(6)	9	(8)	15	(15)
OB	3	(3)	4	(4)	7	(6)	9	(9)	16	(16)
Quosh	2	(3)	4	(4)	6	(6)	9	(9)	16	(15)
Kia-Ora	2	(3)	4	(4)	6	(7)	8	(9)	16	(16)
RB	2	(3)	4	(4)	6	(7)	8	(9)	16	(16)
Corona	3	(3)	4	(4)	6	(7)	9	(9)	17	(16)
Average	2	(3)	4	(4)	6	(7)	9	(9)	16	(16)
Private Labels										
Sainsbury	2	(2)	3	(4)	5	(6)	7	(8)	14	(14)
OBPL	2	(2)	4	(4)	6	(6)	8	(9)	14	(15)
Tesco	3	(3)	4	(4)	7	(7)	10	(9)	17	(16)
Coop	3	(3)	4	(4)	6	(7)	8	(9)	15	(16)
Average	3	(3)	4	(4)	6	(7)	8	(9)	15	(15)

Note : average 24 week base used in fitting the Dirichlet model.

The model predictions are close for brands and private labels and the 48 week averages are predicted exactly (after rounding). Across all 5 product fields, private labels and brands have the same average product purchase rates and both are a little higher than predicted, 20% (18%) and 20% (19%) respectively (Table 4.14).

Table 4.14 : Average Product Purchase Rates For The Average Brand And Private Label For Five Product Fields (48 weeks)

Product Region Field		Brands		Pls	
		O	T	O	T
Squash	Lon	16	(16)	15	(15)
	Lan	20	(20)	22	(21)
Fab. Cond	Lon	9	(9)	8	(10)
	Lan	9	(9)	9	(10)
Beans	Lon	43	(37)	46	(37)
	Lan	44	(39)	42	(40)
Coffee	Lon	15	(14)	16	(14)
	Lan	17	(16)	18	(16)
Washg.	Lon	13	(10)	11	(10)
	Lan	15	(13)	16	(13)
Average		20	(18)	20	(19)

Note: average 24 week base used in fitting the Dirichlet model; Lon - London, Lan - Lancashire.

The Baked Beans figures are higher than for any other product field because they are bought more often; over 30 times in 48 weeks, which is three times more than coffee for example (see Table 1.2 page 32 for details). This is so for both brands and private labels.

Product field buying rates by private label buyers are therefore similar to those for brands, even before allowing for differences in market share. The observed rates are equal, and this is confirmed by the closeness of the Dirichlet model fit. This means that though private label buyers are heavier

buyers of that particular item, they are not heavier buyers of the product field. The high private label w does not seem to show through in product buying rates. This is because most private label buyers also buy brands (see Table 4.20 page 118), and so the high private label w is compensated for by a lower brand w. Together, the two cancel each other out to a large extent.

We have seen earlier how many purchases of a specific item are made (w_x), and now how many of the product field (w_{px}). The proportion of purchases devoted to one particular item is now examined. This is called the "share of requirements", and is calculated from w_x / w_{px} .

Share Of Requirements

In Table 4.13, Sainsbury buyers made 14 Fruit Squash purchases in 48 weeks. However, only 6.6 were of the Sainsbury private label (Table 4.2 page 88), the majority, 7.4 were of other items. This is indicative of the amount of multi-item buying in this product field, which is by no means unusual. The range of items purchased is referred to as the buyer's purchase repertoire. The proportion of the purchase repertoire devoted to one particular item is the share of requirements.

We have already shown that private labels have a higher rate of buying than the average brand and than is predicted from theory. Yet their rate of product field buying is in line with the theory. This therefore affects the share of requirement ratio (shown in the final column of Table 4.15). On average private label buyers devote over a third of their purchases to the one private label as compared to less than a quarter by the average brand buyer. This suggests private label buyers in this product field are more loyal in this respect than are brand buyers.

Table 4.15 : Observed And Theoretical Share Of Requirements Ratio For Fruit Squash [(wx/wpx) * 100] (London 48 weeks)

	wx		wpx		wx/wpx	
	O	T	O	T	O	T
Brands						
Robinsons	3.8	(4.5)	15	(15)	25	(30)
OB	2.8	(4.1)	16	(16)	18	(26)
Quosh	3.7	(4.2)	16	(15)	23	(28)
Kia-Ora	2.8	(4.2)	16	(16)	18	(26)
RB	3.3	(3.9)	16	(16)	25	(23)
Corona	4.0	(3.7)	16	(16)	25	(23)
Average	3.4	(4.1)	16	(16)	22	(26)
Private Labels						
Sainsbury	6.6	(5.3)	14	(14)	47	(38)
OBPL	3.9	(4.5)	14	(15)	28	(30)
Tesco	5.4	(4.1)	17	(16)	32	(26)
Coop	5.2	(3.9)	15	(16)	35	(24)
Average	5.3	(4.5)	15	(15)	36	(30)

Note : average 24 week base used in fitting the Dirichlet model.

Across all five product fields, private label buyers devote a somewhat higher share of their purchases to one private label than the average brand and than is predicted from theory; 32% (28%) and 24% (31%) (figures derived from Tables 4.3 and 4.14 pages 89 and 109).

Therefore, on average private label buyers devote a somewhat higher share of their requirements to a specific private label than does the average brand buyer and than is predicted from the model. However, this is a direct result of the higher average purchase frequency (Table 4.3) because the rate of product field buying is much as predicted (Table 4.14). Apart from this there are no other differences in product field buying between brands and private labels.

Within this average share of requirements ratio, people differ. Some are completely loyal to one item, whereas others switch between different items quite liberally. Together sole and multi-item buyers comprise all buyers and are examined next to complete our analysis of product field buying. We examine whether the private label purchase rate is consistently high for sole and

duplicate buyers, and look for other differences between brands and private labels in respect of their product field buying.

Sole Buying

Sole buyers include those who only bought once, who are sole buyers by definition, as well as those who bought more than once, yet still remained 100% loyal to one item. Analyses have only been undertaken for Fruit Squash and Fabric Conditioner in London and Lancashire because sole buying data was unavailable for the other three product fields. This needs to be borne in mind when interpreting the results. Nevertheless, results can still be generalised to some extent because the two product fields have different private label shares and the regions differ in their retail composition.

Incidence of Sole Buying

The incidence of sole buying is denoted as bsx for item x .

Usually it is found that in short time periods there are many sole buyers because consumers have few opportunities to switch. But as the time period lengthens, values of bsx decline because the opportunities for buying other items increases. Items with small market shares usually have fewer sole buyers than larger ones (Ehrenberg 1972, 1988).

Private label buyers follow these patterns (Table 4.16). The incidence of private label sole buying falls over time from an average of 61% in 4 weeks to 13% in 48 weeks. The rate of fall is around 80%, and this is the same as for the average brand during the same time period. Larger private labels tend to have a higher incidence of sole buying than smaller ones.

Table 4.16 : Observed And Theoretical Incidence of Sole Buyers For Fruit Squash (London) (bs)

weeks	4		8		12		24		48	
	O	T	O	T	O	T	O	T	O	T
Brands										
Robinsons	50	(50)	35	(35)	23	(24)	16	(19)	10	(12)
OB	49	(48)	32	(33)	17	(21)	11	(16)	11	(10)
Quosh	57	(48)	35	(34)	23	(22)	16	(17)	10	(11)
Kia-Ora	44	(47)	30	(32)	20	(21)	15	(16)	8	(10)
RB	53	(46)	40	(32)	26	(20)	26	(15)	19	(10)
Corona	62	(45)	56	(31)	44	(19)	38	(15)	27	(9)
Average	53	(47)	38	(33)	26	(21)	20	(16)	14	(10)
Private Labels										
Sainsbury	74	(55)	60	(41)	43	(29)	35	(24)	19	(16)
OBPL	60	(50)	44	(36)	33	(24)	29	(19)	16	(12)
Tesco	56	(48)	36	(33)	21	(21)	12	(16)	8	(10)
Coop	52	(47)	41	(32)	29	(21)	25	(16)	8	(10)
Average	61	(50)	45	(36)	32	(24)	25	(19)	13	(12)

Note : average 24 week base used in fitting the Dirichlet model.

The Dirichlet model under-predicts the incidence of sole buying in short time periods, but is closer in 48 weeks. This deviation affects all items similarly (excluding Corona) and so does not affect the main brand/private label comparison. There are some larger deviations for the smaller brands which are mainly due to small sample sizes.

Private labels are predicted to have a similar incidence of sole buying to brands, (12%) and (10%) respectively, in 48 weeks. Both brands and private labels attract slightly more sole buyers than predicted in 48 weeks; 14% (10%) and 13% (12%) respectively and so do not differ in this respect.

Across both the product fields examined here, private labels have the same incidence of sole buying as brands. Both are closely predicted by the Dirichlet model in longer time periods and have similar discrepancies in shorter ones (Table 4.17).

Table 4.17 : Incidence Of Sole Buying For The Average Brand And Private Label For Two Product Fields

weeks	Region	4				48			
		brand		pl		brand		pl	
		O	T	O	T	O	T	O	T
Squash	Lon	53	(47)	61	(50)	14	(10)	13	(12)
	Lan	48	(39)	46	(37)	9	(7)	10	(6)
Fab Con.	Lon	81	(68)	79	(65)	18	(23)	22	(23)
	Lan	85	(69)	83	(65)	21	(25)	20	(19)
Average		67	(56)	67	(54)	16	(16)	16	(15)

Note : average 24 week base used in fitting the Dirichlet model.

In short time periods Fabric Conditioner has a high incidence of sole buying in absolute terms. This is because it is seldom bought (Table 4.14) and so buyers do not have as much opportunity to switch as when buying Fruit Squash.

These results show that for the two product fields examined the incidence of sole buying by private label buyers is similar to that for brand buyers. Not only are the theoretical predictions similar in 48 weeks, but the observed figures are the same. This means that private labels do not attract any more or less sole buyers than any other item with a similar market share despite being unique to a particular store. Nor does the high private label purchase rate seem to show through in the incidence of sole buying.

We now examine the rates of buying by these sole buyers.

Purchase Frequency of Sole Buyers

This is equivalent to their total product purchasing since they do not buy other brands. The purchase frequency of sole buyers is denoted as w_x for item x . Sole buying rates also tend to have a Double Jeopardy effect and vary little within the same time period.

Private label Fruit Squash buyers are predicted to have a slightly higher rate of sole buying than the average brand; (2.3) and (2.6) times respectively in 48 weeks (Table 4.18). This is a result of their high purchase frequency identified

earlier (Table 4.2).

However in addition to this, they have a much higher rate of sole buying than predicted. In 48 weeks, the average private label sole buyer made 5.5 purchases which is 110% higher than the (2.6) predicted. Even without the unusually high Sainsbury sole buying rate of 8.3, the average is still nearly 80% higher than predicted. Brand sole buying rates are also higher than predicted, but the difference is smaller, 26%, and less systematic than that for private labels.

Table 4.18 : Observed And Theoretical Average Purchase Frequency of Sole Buyers For Fruit Squash (London) (ws)

weeks	4		8		12		24		48	
	O	T	O	T	O	T	O	T	O	T
Brands										
Robinsons	1.4	(1.4)	1.7	(1.6)	2.1	(1.9)	2.2	(2.1)	2.8	(2.6)
OB	1.3	(1.3)	1.6	(1.5)	1.9	(1.8)	1.3	(2.0)	1.5	(2.3)
Quosh	1.5	(1.3)	1.9	(1.6)	2.6	(1.8)	2.9	(2.0)	4.1	(2.4)
Kia-Ora	1.2	(1.3)	1.4	(1.5)	1.5	(1.7)	1.8	(1.9)	2.9	(2.2)
RB	1.4	(1.3)	1.5	(1.5)	2.0	(1.7)	2.2	(1.9)	2.4	(2.2)
Corona	2.1	(1.3)	2.5	(1.5)	4.1	(1.7)	2.5	(1.8)	3.7	(2.1)
Average	1.5	(1.3)	1.8	(1.5)	2.4	(1.8)	2.2	(2.0)	2.9	(2.3)
Private Labels										
Sainsbury	1.7	(1.4)	2.5	(1.7)	3.9	(2.1)	5.5	(2.5)	8.3	(3.1)
OBPL	1.5	(1.4)	1.9	(1.6)	2.5	(1.9)	2.8	(2.1)	3.3	(2.6)
Tesco	1.8	(1.3)	2.4	(1.5)	3.9	(1.8)	4.4	(2.0)	5.0	(2.3)
Coop	1.8	(1.3)	2.0	(1.5)	2.8	(1.8)	2.5	(1.9)	5.5	(2.2)
Average	1.7	(1.4)	2.2	(1.6)	3.3	(1.9)	3.8	(2.1)	5.5	(2.6)

Note : average 24 week base used in fitting the Dirichlet model.

The rate of sole buying in longer time periods by Sainsbury private label buyers is unusually high in this data set. This is largely because they are very heavy buyers of the private label (Table 4.2). However, even taking this into account, the Sainsbury rate still seems to be somewhat high in comparison to the other private labels. Differences between the private labels of individual stores are discussed in more detail in chapter 6.

Across the other product field, private labels are also found to have a much

higher rate of sole buying than predicted; the average private label reading is 1.9 points, or over 80% higher than the theoretical as compared to 0.5 points or 20% higher for the average brand (Table 4.19).

Table 4.19 : Observed And Theoretical Rate Of Buying By Sole Buyers For The Average Brand And Private Label For Two product Fields

weeks	Region	4				48			
		brand		pl		brand		pl	
		O	T	O	T	O	T	O	T
Squash	Lon	1.4	(1.3)	1.5	(1.4)	2.9	(2.3)	5.5	(2.6)
	Lan	1.6	(1.4)	1.4	(1.3)	2.9	(2.2)	4.8	(2.0)
Fab Con.	Lon	1.3	(1.3)	1.1	(1.3)	2.8	(2.8)	2.8	(2.5)
	Lan	1.3	(1.3)	1.2	(1.3)	2.9	(2.2)	3.5	(2.0)
Average		1.4	(1.3)	1.3	(1.3)	2.9	(2.4)	4.2	(2.3)

Note : average 24 week base used in fitting the Dirichlet model.

The high rate of buying by private label buyers generally (Table 4.3) shows through here as a particularly high rate of sole buying. The difference is more pronounced in Table 4.19 because it is diluted to some extent in the summary measure of which the sole buying rate is just one part.

In summary, the incidence of private label sole buying is similar to that for brands, and both are closely predicted by the model in longer time periods. The high private label w does not show through in the incidence of sole buying as one might have expected intuitively. However, private label sole buyers have a much higher rate of purchasing than brand buyers and than is expected from theory. This is a contributory factor to their higher than expected overall average purchase frequency which was identified in Table 4.3.

It is interesting that the high private label w shows through entirely in the rate of sole buying, rather than in both the number of sole buyers and their rate of buying. Such issues are discussed in more detail in section 4.3 and then in the discussion in chapter 9.

We have seen that private label sole buyers have a higher rate of buying than predicted. We now need to examine duplicate buyers, who switch between items in the product field to complete our analyses of product field purchasing.

Duplicate Buying

We already know that most buyers buy more than one item in the product field because the rate of product field purchasing (Table 4.14) is greater than the rate of item buying (Table 4.3). We also know that most buyers have a repertoire of purchases and give a certain share of their requirement to each item (Table 4.15). Indeed, it has just been shown that on average only 16% of buyers remain loyal to a single item in 48 weeks (Table 4.17) which means the majority of buyers spread their purchases across the product field in longer time periods.

In this section the discussion centres on which others are also bought and in what proportions. Duplication analyses enable us to examine how these product field purchases are allocated between individual items. Those who buy more than one item in a given time period are referred to as **multi-brand or duplicate buyers**.

Incidence of Multi-Brand Buyers

This is denoted as bdx for item x .

Table 4.20 shows the proportion of item X buyers who also bought item Y in 48 weeks. Abbreviations across the top of the table reflect items listed down the side. First the general idea of duplication is introduced before focussing on the private label/brand comparison. Brands and private labels are ordered by their penetration levels with larger items first. Table 4.20 reads as follows: 40% of Robinsons buyers also bought other brands (OB), 35% of Robinsons buyers also bought Quosh etc.

**Table 4.20 : Observed Incidence of Duplicated Buying For Fruit Squash
(London (bdx) 48 weeks)**

	Who also bought:									
	RO	OB	QU	KI	RB	CO	SA	OB	TE	CO
Buyers of:										
Brands										
Robinsons	*	40	35	31	16	7	46	43	19	11
OB	53	*	41	31	14	8	46	50	18	14
Quosh	49	44	*	31	17	5	36	41	22	17
Kia-Ora	58	44	40	*	20	4	37	44	16	15
RB	43	29	32	29	*	3	37	38	18	10
Corona	50	38	36	30	16	*	39	42	20	14
Average	51	39	37	31	17	5	40	43	19	13
Private Labels										
Sainsbury	43	33	24	19	13	4	*	42	13	7
OBPL	42	37	28	23	14	5	44	*	19	11
Tesco	49	35	40	22	17	4	36	51	*	14
Coop	39	37	43	29	14	4	27	41	20	*
Average	43	36	34	23	15	4	36	45	17	11
Average Penetration	47	37	35	27	16	5	39	44	18	12
	29	22	20	15	10	3	30	29	11	8
										Overall Avge. 28.0
										Overall Avge. 17.7

There are again some regular buying patterns; usually it is found that the incidence of duplication is positively related to penetration, so that a larger item attracts more multi-brand buyers than a smaller one; and that figures within each column vary little (Ehrenberg 1972, 1988).

This means that in fast moving consumer goods markets there is often no apparent market segmentation. For example, it may be expected that people who buy private labels would be more inclined to buy other private labels also, thus reflecting some kind of "private label proneness", or that people are particularly loyal to the private labels of certain stores. The duplication analysis enables us to examine such issues in detail.

The theoretical predictions used in this section are not from the Dirichlet model. Instead a simple duplication law is used. This is because the duplication

law is simpler and easier to communicate; and it has been found to accurately predict the incidence of brand duplication on many occasions (Ehrenberg 1972, 1988).

It is derived as follows. First we calculate a coefficient of duplication "D", which is the average duplication (28%) divided by average penetration (17.7%) (Table 4.20). It provides an index of the relationship between the two variables. For Fruit Squash (London) the duplication coefficient is 1.6.

$$D = \text{Coefficient of Duplication} = 28 / 17.7 = 1.6$$

If purchasing of two items is independent (ie. purchasing X does not influence the buyers likelihood of buying Y), then $D = 1$. If $D < 1$ there is negative correlation between purchasing the two items so that purchasing one inhibits the other. If $D > 1$ the opposite occurs. Therefore, a duplication coefficient of 1.6 means the proportion of item X buyers who also buy Y is greater than the proportion of all consumers who buy Y. Indeed item X buyers are 60% more likely to also buy Y than are buyers of Y in the population generally.

The D coefficient is then multiplied by the penetration for each item to provide a theoretical estimate. Theoretical predictions for the overall average incidences of duplication for the product field are shown in the penultimate line of Table 4.21. Duplication for each quadrant of the table has also been calculated because this is particularly relevant to the question of private label proneness which we discuss below.

Table 4.21 : Observed And Theoretical Incidence of Duplicated Buying For Fruit Squash (London (wdx) 48 weeks)

	Who also bought: Brands						Private Labels				D Coefficient	
	RO	OB	QU	KI	RB	CO	SAOBP	TE	CO			
% Buyers of:												
Robinsons	*	40	35	31	16	7	46	43	19	11		
OB	53	*	41	31	14	8	46	50	18	14		
Quosh	49	44	*	31	17	5	36	41	22	17		
Kia-Ora	58	44	40	*	20	4	37	44	16	15		
RB	43	29	32	29	*	3	37	38	18	10		
Corona	50	38	36	30	16	*	39	42	20	14		
Average Predicted *1	51	39	37	30	17	5	40	43	19	14	1.8	1.5
	52	40	36	27	18	5	45	44	17	12		
Sainsbury	43	33	24	19	13	4	*	42	13	7		
OBPL	42	37	28	23	14	5	44	*	19	11		
Tesco	49	35	40	22	17	4	36	51	*	14		
Coop	39	37	43	29	14	4	27	41	20	*		
Average Predicted *1	43	36	34	23	15	4	36	45	17	11	1.6	1.4
	46	35	32	24	16	5	42	41	15	11		
Overall Avge Overall Pred *2	47	37	35	27	16	5	39	44	18	12	1.6	
	46	35	32	24	16	5	47	46	17	13		
Deviation	1	2	3	3	0	0	(8)	(2)	1	1		

Note: *1 Predicted duplication based on D coefficient for each quadrant.

*2 Predicted duplication based on D coefficient for product field.

Generally, private labels conform to the usual patterns of duplicate buying. Average overall duplication for private labels falls from 39% to 12% in line with a fall in penetration (Table 4.2). Figures within each column vary little.

Duplication across the product field is similar for brands and private labels (except for Sainsbury) and largely in line with the theoretical predictions. This means there is no apparent sign of any market segmentation between brand and private label buyers. Duplication with the Sainsbury private label is 8

points below the predicted value, 39% (47%) because its buyers devote such a high share of their purchases to it that there are few other purchases to distribute across the product field (Table 4.15). However the size of this discrepancy does not generalise to other private labels, nor to other Sainsbury private labels.

We might expect there to be some evidence of private-label-proneness, ie a tendency for private label buyers to be more inclined to buy another private label than a brand. This would show through as high duplication coefficient within the private label segment (1.4) and a lower duplication coefficient in the brand/private label segment (1.6, 1.5). But we find duplication coefficients are much the same. Indeed, the predicted duplication within each segment is close to the observed figures and much the same as that for the product field.

Furthermore, across both product fields examined there is no strong evidence of any brand/private label segmentation (Table 4.22). Duplication coefficients vary unsystematically by data set so we comment on the average below.

Duplication between private labels is much the same as that between brands with D coefficients of 1.8 and 1.9 respectively (Table 4.22). Furthermore, these are usually slightly higher than D coefficients in the brand/private label segments. This suggests some buyers are slightly more prone to restricting their purchases to either brands or private labels rather than switching between them.

However, the fact that the private label duplication coefficient is similar to the brand coefficient may seem surprising given that private labels are only available in one specific store chain. More effort is therefore required to switch between different stores' private labels. Though we know that most consumers visit more than one store chain for their grocery purchases (Kau 1981, Kau and Ehrenberg 1984, Uncles and Ehrenberg 1988, Ellis and Uncles 1989 Appendix 12). When a buyer is in Sainsbury, she cannot buy the Tesco private label, and so the opportunity to buy is reduced.

Those who switch between brands and private labels, do so to the same extent with D coefficients of 1.6. There is no sign that purchasing private labels inhibits brand purchases or vice-versa.

Table 4.22 : Duplication Coefficients For The Average Brand and Private Label In Two Product Fields (48 weeks)

			brands	pls
Squash	London	br	1.8	1.5
		pl	1.7	1.4
	Lancs	br	1.5	1.3
		pl	1.3	1.8
Fab. Cond	London	br	2.6	1.4
		pl	2.2	1.6
	Lancs.	br	1.7	1.5
		pl	1.6	2.2
Average	br	1.9	1.6	
	pl	1.6	1.8	

Therefore, on the whole people buy brands and private labels interchangeably and do so much in line with their relative market shares. There is no strong evidence of a group of particularly loyal private label buyers who for example, never buy brands. Though there is some slight evidence that some buyers restrict their purchases to brands and others to private labels, they do so to the same degree. These results suggest that items are bought as though they were no different other than in their levels of market share. The high private label purchase frequency does not show through in the incidence of duplicate buying.

We now examine the rate of duplicate buying.

Average Purchase Frequency of Duplicated Buyers (wdx)

The rate of buying by duplicate buyers is denoted as wdx for item x. Generally the rate of duplicate buying is higher than the rate of buying by all buyers and varies little within a column. Table 4.23 reads as follows; buyers of Robinsons who also bought other brands (OB), bought OB 4.8 times in 48 weeks; those who also bought Quosh, bought Quosh 4.3 times etc.

Table 4.23 : Observed Average Purchase Frequency of Duplicated Buyers For Fruit Squash (London (wdx) 48 weeks)

	Who also bought : Brands						Private Labels			
	RO	OB	QU	KI	RB	CO	SA	OB	TE	CO
Buyers of :										
Brands										
Robinsons	*	4.8	4.3	5.3	3.7	4.3	4.2	4.2	4.7	2.6
OB	3.5	*	3.6	2.5	5.2	3.1	2.5	3.4	4.2	3.3
Quosh	3.5	4.0	*	3.9	4.2	3.3	3.0	3.7	3.6	4.5
Kia-Ora	2.9	3.5	3.7	*	3.2	3.0	3.3	2.8	2.3	3.6
RB	4.3	3.2	2.6	3.8	*	3.2	4.6	3.7	3.4	3.1
Corona	2.9	3.3	3.2	3.5	2.9	*	2.9	3.4	3.5	2.4
Average of quadrant						3.6	3.5			
Private Labels										
Sainsbury	6.2	5.9	5.2	5.3	4.3	4.2	*	6.7	4.4	6.0
OBPL	4.1	5.5	4.1	3.9	4.9	4.5	3.5	*	4.5	3.3
Tesco	5.9	4.6	7.1	8.4	8.3	4.9	4.3	5.6	*	3.9
Coop	6.3	6.4	7.6	6.7	14.1	6.0	4.0	7.7	6.1	*
Average of quadrant						6.0	5.0			
Average	4.6	4.7	4.8	5.0	6.0	4.1	4.7	4.7	4.2	3.8
*						4.8				4.1
wx	3.8	2.8	3.7	2.8	3.3	4.0	6.6	3.9	5.4	5.2
Deviation	0.8	1.9	1.1	2.2	2.7	0.1	(2.9)	0.8	(1.2)	(1.4)

* These are the overall averages of the duplicate buying rates for brands (4.8) and private labels (4.1).

There is some variation within the columns due mainly to small sample bases, but this occurs for both brands and private labels. We also find that private label duplicate buying rates are slightly lower than the average rate of buying by all private label buyers, 4.1 and 5.3 (average of wx for private labels) respectively. This is the opposite to brands and to what is usually found (Ehrenberg 1972, 1988). This again shows that private label buying rates are high.

On average duplicate buyers who buy private labels do so less frequently than those who also buy brands, 4.1 and 4.8 respectively. This is the opposite to the high rate of sole buying by private label buyers identified earlier (Table 4.19), but the difference here is smaller than for sole buying rates so the overall private label purchase rate still shows through as being high.

Duplicate rates within the private label segment are higher than those within the brand segment, 5.0 and 3.6 respectively. This suggests that those who concentrate their purchases on private labels are heavier buyers than those who concentrate on brands.

Rates of private label duplicate buying are on average lower than for the brands and below buying rates by all private label buyers. However, within the private label segment, rates are higher than within the brand segment. This means that the high private label w is mainly a result of high sole buying rates by private label sole buyers, and less so from buying rates within the private label segment. There is no strong evidence of brand or private label segmentation in respect of their purchase rates.

Summary

Product field buying rates by private label buyers are much the same as for brand buyers. Though private label buyers are heavier buyers of the specific private label, they are not heavier buyers of the product field more generally. This is because the high private label purchase rate is compensated for by a lower brand purchase rate. Product field purchasing is therefore similar for brands and private labels.

As a direct result of their high average purchase frequency and expected rate of product field buying, the share of requirements given to specific private labels is higher than for the average brand, and than is predicted by the Dirichlet model.

The incidence of sole buying for private labels is much the same as for brands and both are similarly predicted by the Dirichlet model. Private labels do not therefore attract more loyal buyers in this respect than any brand with a comparable market share. However, it must be borne in mind that only two product fields in two regions have been examined here. The rate of buying by these sole buyers is on average 83% higher than predicted by the Dirichlet

model and over 40% higher than for the average brand. This is therefore a contributory factor to the high rate of private label buying more generally.

The incidence of private label duplication is largely in line with theoretical predictions from the duplication law. People buy brands and private labels interchangeably, and do so largely in line with their market share levels. There is no firm evidence of any market segmentation between brands and private labels, and duplication coefficients are similar for both.

Rates of buying by private label duplicate buyers are slightly lower than for brands, and below the rate of buying by all private label buyers. There is no sign of a particularly heavy group of private label buyers. This does not therefore contribute to the high rate of private label buying generally except in so far as those who remain in the private label segment are slightly heavier buyers than those who remain in the brand segment.

The high rate of private label buying identified earlier (Table 4.3) shows through primarily in the rates of buying by sole buyers. This is diluted to some extent in the summary measure of the average purchase frequency because of the inclusion of duplicate buyers.

4.3 SUMMARY AND CONCLUSIONS

Despite all the complexities surrounding the purchase behaviour of fast moving consumer goods, many highly regular patterns have been observed. The regularities are not new, they are well established patterns (Ehrenberg 1972, 1988). Moreover, most of these regularities can be predicted by existing brand choice models such as the NBD, and brand choice and purchase incidence models such as the Dirichlet. In this chapter we have shown that now these well established research tools can on the whole be applied to a new and quite different set of data. They can be applied to private labels, which hitherto, have not been examined explicitly.

On some occasions though, the model predictions are deviant. These include general product field deviations and those relating to private labels in particular. For example the incidences of repeat buying are consistently poorly predicted by the NBD model, and this also occurs in the analyses in chapters 6 and 7; and the incidence of sole buying is consistently under-predicted in short time periods. The latter deviation is consistent and occurs systematically across the two product fields examined and so it does not directly affect the main brand/private label comparison.

Observed data can still be compared with the theoretical predictions once having accounted for such deviations. However, the repeat buying deviation varies by product field. In these circumstances, it is difficult to interpret the results in any substantive manner. Though these deviations are interesting, they are not examined in detail because they are outside the scope of the thesis. Instead we concentrate on those deviations which are relevant to our study of private labels.

The main objective of this chapter was to establish whether people buy private labels in the same way as brands, and whether they do so in line with the theory of buyer behaviour used. Results show that private labels are bought in much the same way as brands, and that the fundamental patterns of buyer behaviour which have been observed for brands, do on the whole apply to private label purchasing. However, there are some differences which occur on average across the product fields examined. The differences and similarities are summarised below, but the main discussion and interpretation is left for chapter 9.

The Components Of The Sales Equation Differ For Brands And Private Labels

- * On average private labels have a purchase frequency which is 17% higher than that predicted by the Dirichlet model, as compared to the average brand which is 13% below. This means that even after allowing for differences in market shares, private labels are bought more frequently than are brands in general.
- * The nature of the Dirichlet model is such that the high private label w is compensated for by a lower b . Private label penetration is 14% lower than predicted as compared to the average brand being 11% higher than predicted.
- * This result is robust. It holds on average across 5 product fields; two regions; for different length time periods; and was also found to occur in data from over 20 years ago. The difference is supported theoretically by the Dirichlet and NBD models and also when we allow directly for market share using the simple sales equation model, $w(1-b)$.
- * This deviation is on the whole equally split between b and w . In London the private label w is much higher than predicted; in Lancashire the model fit is closer. Apart from these, the size of variations in b and w

are similar in both regions.

- * The NBD model predictions for period to period buying and the purchase frequency distribution, show that once this difference in the components of the sales equation is taken into consideration, there are no other differences in brand and private label purchase behaviour.
- * This difference has repercussions on other measures of buyer behaviour but there is no research on how deviations affect other measures of buyer behaviour, so these are new results. The high private label w shows through as a higher incidence of repeat buying and a slightly higher rate of buying than brands; the share of requirements ratio is also higher than for brands; and rates of buying by sole buyers are extremely high. These are discussed in more detail below.

Period To Period Buying Is Similar For Brands And Private Labels

- * This section was limited because the NBD model was shown to deviate unsystematically across the product field, making interpretations difficult. However, it seems from the observed data that patterns of period to period buying are similar for brands and private labels. The only difference between them was that private labels seemed to have a slightly higher rate of repeat buying which was not matched by brands.
- * The high private label w shows through in the observed values as a higher incidence of repeat buying and slightly higher rate of buying than brand buyers. The corollary being fewer new and lapsed buyers, but where rates of new and lapsed buying were similar to those for brands.

Private Label Buyers Have A Similar Purchase Frequency Distribution To Brand Buyers

- * Private labels have a similar positively skewed purchase frequency distribution to brands. Both are closely predicted by the NBD model with a slight surplus of light buyers and a shortfall of medium and heavy buyers on average. The closeness of fit reinforces the point that once differences in w are taken into account, private labels are bought much like brands in this respect.

- * The high private label w does not show through here because it is equally distributed over the population of buyers. Also it is taken into account in the model specification.

Private Label Buyers Are Not Heavier Buyers Of The Product Field

- * Though private label buyers buy more of the specific item, their overall rate of product field buying is much the same as for brands, and both are closely predicted by the Dirichlet model.
- * The high private label w does not show through here because most private label buyers in long time periods also buy brands. So the high private label w is compensated for by a lower brand w . Together these cancel each other out.

Private Label Buyers Have A Slightly Higher Share Of Requirements Ratio

- * As a direct result of the high rate of buying by private label buyers, coupled with their as expected rate of product field buying, their share of requirements is higher than the average brand. This is also higher than the model predictions.

Private Labels Buyers Are Very Heavy Sole Buyers

- * Patterns of sole buying are on the whole similar for brands and private labels. However, only two product fields have been examined here which limits the robustness of the results.
- * On average the incidence of sole buying by private label buyers is similar to that for brands. Not only are the theoretical predictions similar, but the observed figures are the same when averaged across the two product fields. So private labels do not attract any more or less sole buyers than any other item with a similar market share despite being store specific.
- * However, rates of buying by these buyers are much higher than predicted. Across both product fields in 48 weeks rates are over 80% higher than predicted and 40% higher than the average brand, despite predictions for the average brand and private label being similar.

- * Even after allowing for market share differences, private labels have a higher rate of sole buying which seems to be the main contributor to their high rate of buying generally. The extent of this discrepancy is diluted somewhat in the summary measure because of the inclusion of many duplicate buyers.
- * The high private label w shows through almost entirely in the rate of sole buying, rather than the incidence. This is discussed more fully in chapter 9.

There Is No Strong Evidence Of Private Label Proneness

- * The incidence of duplication is similar for brands and private labels. On the whole people buy them interchangeably and do so much in line with their market shares. There is only a slight indication of market segmentation between brand and private label buyers in that private label buyers are as likely to buy other private labels as are brand buyers other brands. Duplication here is slightly higher than for those who switch between brands and private labels.
- * The fact the private label duplication coefficient is as high as that for brands may seem surprising given that private labels are store specific. More effort is required to switch between private labels because this involves a change of store. Though we know that people switch between stores for their grocery purchases, the opportunity to buy the private label is still somewhat lower than for the average brand.
- * These results suggest that there is little market segmentation between brands and private labels. They are bought interchangeably as though the only difference between them was their market share level.
- * Rates of duplicate buying by private label buyers are lower than for brand buyers and below rates of private label buying generally. So there is no evidence of a group of heavy private label buyers.

Therefore, the main difference in the way in which people buy private labels and brands is that private labels are bought more frequently by fewer people than the average brand and than is predicted in theory. This means that for a

brand and private label with the same penetration, the private label will have a higher market share because it is bought more often. This finding is robust. It has repercussions on other related measures of buyer behaviour such as the share of requirement ratio, incidence and rate of repeat buying, and rates of sole buying.

The high rate of buying shows through in the rate of sole buying. However, why only sole buying rates are high, rather than duplicate buying rates, or the incidences of both is an interesting question. We try and provide some reasons for this in chapter 9.

In addition to the high private label purchase frequency, there are three other results. First that though private label buyers are heavy item buyers they are not heavier buyers of the product field in general. Second, sole private label buyers have a much higher rate of buying than is predicted and than the average brand whereas duplicate rates are lower. Third, that rates of period to period buying are slightly higher for private labels than brands and than is predicted. These additional deviations from the model vary in their size and consistency. However they are sufficiently consistent and of enough managerial significance to warrant further investigation.

Despite these interesting sub-patterns which are more fully discussed and accounted for in chapters 5, 6 and 7, private labels are bought in much the same way as brands. Their underlying structure is similar and can on the whole be predicted by the NBD and Dirichlet models. Overall private labels follow the same basic patterns that have been established for brands despite the apparent differences (price, distribution etc) between them.

However, the important difference from the theoretical predictions is the composition of the sales equation, which is examined and largely accounted for in Chapter 5. The other differences are explored further at the within store level in Chapter 6 and also in Chapter 7. These are not major differences from brand buying patterns, but are sufficiently large and consistent to warrant further investigation.

**CHAPTER 5 :AN ANALYSIS OF THE HIGH PRIVATE LABEL AVERAGE PURCHASE
FREQUENCY**

5.1 Introduction**5.2 Outline Of Possible Explanations**

- 5.2a Private Label Limited Availability
- 5.2b Other Explanations

5.3 Population At Risk

- 5.3a The Problem
- 5.3b Differences In The Availability Of Private Labels and Brands

5.4 Accounting For The High Private Label Purchase Frequency**5.4a Estimating A More Relevant Population At Risk**

- A Conservative Estimate - Fruit Squash (London) Buyers
- A More Liberal Estimate - Buyers Of 73 TCA Product Fields
- A Theoretical Dirichlet Estimate
- Comparing The Three Estimates
- Summary

5.4b Supporting Analyses

- A Mega-Private Label
- Purchasing Within Store Chains
- OBPL Overcomes Limited Distribution
- Other Research
- Summary

5.5 Market Segmentation**5.6 Summary And Conclusions**

5.1 INTRODUCTION

In Chapter 4 it was shown that the main difference between brands and private labels was that private labels had a somewhat higher average purchase frequency than was predicted by the Dirichlet model. In addition, there was another difference relating to their rate of buying by sole private label buyers which is dealt with in chapters 6 and 7. The objective of this chapter is to determine why private label buyers have a high rate of buying and to try and account for the discrepancy.

It is important that we can explain this discrepancy before continuing with our private label study. This is because in Chapter 4 it was shown that the deviation has repercussions on other measures of buying behaviour. This means that we cannot separate such effects from other private label results. For example, there may be other private label differences which do not show through these repercussions. Therefore, much emphasis is given to explaining the deviation before continuing with the main study.

There are many possible reasons for private label buyers having a higher rate of buying. The main question we address is does it mean there is greater loyalty to private labels, or is it due to some other factor which differs for private labels? There are many differences: private labels are not directly advertised in the same way as brands; they tend to be cheaper than brand leaders; and are only available in specific store chains which means they have more limited distribution than the average brand. In fact we find that it is their limited availability which seems to explain the high purchase rate.

The chapter consists of four main sections. In section 5.2, we discuss factors which could in principle account for the private label buying rate. Though the limited availability of private labels in comparison to national brands is shown to largely account for the discrepancy, other explanations were examined. These results are outlined with an explanation of why they are unlikely to be a major cause of the high private label buying rate. These other explanations include differences in the marketing variables and testing the model assumptions of a unsegmented and stationary market.

In section 5.3, we discuss how private label availability affects buyers behaviour calculations and show that private labels do indeed suffer from limited availability in comparison to the average brand.

Then in section 5.4, we try and account for the private label deviation empirically. Various estimates are made of a more relevant buying population for private labels so as to account for the private label deviation. Then further analyses whereby brand and private label availability are more or less equal are undertaken. We find that when availability differences are accounted for, the private label deviation no longer exists.

In section 5.5, market segmentation analyses show that the market is indeed unsegmented which means that this cannot in principle account for the private label deviation. Finally, these results are summarised in section 5.5.

5.2 OUTLINE OF POSSIBLE EXPLANATIONS

Many factors could cause or contribute to the high private label purchase rate, but we find that their limited availability accounts for most of the discrepancy. This explanation is therefore the only one examined thoroughly, though the results from others are outlined.

5.2a Private Label Limited Availability

Private labels are not as widely available as the majority of branded goods. This means that some people on the panel have no access to a specific private label. For example, an individual in Sainsbury has access to various brands and the Sainsbury private label; an individual in Tesco has access to a similar range of brands but can only buy the Tesco private label. So the opportunity to buy specific private labels is more limited than for most brands. Furthermore, if an individual does not have access to a particular store, he will be unable to buy their private label at all. Those who have access are referred to as being in the "Population At Risk".

Conventionally, buyer behaviour statistics are calculated on the basis of an equal potential population of buyers, ie a common population at risk, for all items concerned. However specific private labels are not as widely available as the majority of branded goods, so some of their buyer behaviour statistics are derived from an overstated population of potential buyers. The resulting figures for such as penetration are then underestimated and this has repercussions on other measures. This explanation is discussed in more detail in section 5.3.

5.2b Other Explanations

There are many explanations which could in principle account for the high

private label purchase rate. For example, differences in the marketing mix variables between brands and private labels; a violation of the model assumptions by private labels; or indeed that private labels do in fact attract more loyalty from their buyers in respect of their purchase rate. However, analyses here and other research show that the population at risk explanation largely accounts for the discrepancy.

Therefore, only population at risk analyses are shown in detail. Other explanations were explored and the results of these are shown in summarised form. These other explanations include; marketing mix variables such as price, pack size and the lack of direct advertising support for private labels, then testing the model assumptions of stationarity and market segmentation. There is no past research to show how any differences relate directly to purchase frequency but we suggest how this may occur below.

Marketing Mix Variables

Prices, pack size and the level of advertising support differ for brands and private labels and so could in principle contribute to the private label purchase rate. However, the effects of such differences are not usually large enough to cause departures from the model predictions over and above any direct effect on market share. Indeed the effects of competitive activity and the smoothing effects of longer time periods used in the analyses are not usually sufficient to cause deviations from the model. The fact that the stochastic processes tend to be an accurate description of peoples' purchasing behaviour suggests that in the aggregate competitive activity is reflected in market share and so it does not affect b without w or vice-versa.

Private labels tend to have lower prices than brands on average (Euromonitor 1986, Swan 1974). Studies have shown that price affects market share in fast moving consumer goods product fields where items are weakly differentiated (Gabor 1980, Ehrenberg and England 1987). The fact private labels are cheaper on average could in principle account for the high private label purchase rate. For example, at the point of sale, where people can directly compare prices, they may choose the private label because it is favourably priced and this tends to be highlighted at the point of sale.

However, if such differences in price did affect purchase behaviour, this "exceptional effect" would show up as a consistent deviation from the model

predictions. Limited analyses have been undertaken on the average price paid by each panelist for Fruit Squash and Fabric Conditioner. It was found that private labels were not consistently cheaper than brands. They are usually cheaper than the brand leader, but tend to be more expensive than smaller brands.

So if private label prices were inversely related to purchase rate, their rate of buying would be higher than the brand leader but lower than for smaller brands. This is not what we find. Furthermore, this would run counter to the Double Jeopardy pattern whereby purchase rate is directly related to penetration and market share. So any price effects should be reflected in both b and w .

Pack size differences could also affect the purchase rate in principle. However, analyses for Fruit Squash and Fabric Conditioner show that private labels are available in the same variety of pack sizes as are brands. Also when the data were divided into buyers of small, medium and large pack sizes. It was found that the high private label purchase rate existed to a similar degree in all three subsets. Therefore, this is unlikely to account for the private label purchase rate.

Private labels are not directly advertised in the same way as are brands. Retailers usually advertise via the press to promote prices, and use television advertising for their corporate image. Though private labels are rarely directly advertised in the same manner as are brands, they do receive some form of advertising support (Fulop 1983).

The fact that brands are directly advertised could encourage people to switch more regularly between them, thus reducing each ones purchase frequency. Because private labels do not receive the same kind of advertising support and are promoted more within the store, they could benefit from this brand disloyalty, whilst at the same time their buyers are less inclined to switch. This could in principle affect their purchase frequency.

However, we show that people switch between brands and private labels to a similar degree. Though it is difficult to identify the repercussions of brand advertising directly on the brand itself, let alone its competitors, a study by Chaplin and Watkins (1985) on the Toothpaste and Fruit Squash market found

that brand advertising had no significant impact on private label value or volume share.

Therefore, it seems unlikely that advertising would account for the difference between brand and private label purchase rates.

These provide an indication of which other factors could be influential in the private label purchase rate, and intuitively how the differences might result in a high private label purchase rate. However, we have found no evidence to suggest that any of these may in themselves account for the private label purchase rate. Such factors are subsumed in market share anyway when the model works, so we are really looking for exceptional influences to account for the discrepancy.

Model Assumptions

In addition to marketing mix variables, there are also factors which relate to the model assumptions of stationarity and lack of market segmentation, which have both been examined. The NBD model assumes that the items sales are stationary in the analysis period, and the Dirichlet assumes a stationary and an unsegmented market. If either of these assumptions are not reasonable approximations to what is found in practice, the observed measures for the whole product field could deviate markedly from the theoretical predictions. Moreover, if private label purchase behaviour differed from brand purchase behaviour in respect of these assumptions, this could in principle result in differences in the components of the sales equation.

If brands and private labels had different degrees of stationarity, this could cause deviations from the model predictions. For example, if private label sales were more variable than brands due to in-store promotional activity, this could result in them having a higher average w during the promotional period. Alternatively, brand sales may be more variable, because of advertising and this could result in them having a lower w .

However, analyses (chapter 8) show that in both seasonal and non-seasonal product fields, brand and private label purchase behaviour is similar. The high private label w occurs in stationary and non-stationary product fields. So stationarity is unlikely to account for the systematic difference in the private label purchase rate.

Segmentation refers to a situation where there is high or low duplication between two items over and above what is predicted given their market shares. If for example, there was some sign of "private label proneness" whereby those who bought a particular private label were then more inclined to buy another private label than a brand buyer or member of the general population, this could result in a deviation from the model. However, analyses in section 4.2d (page 107) showed that private labels and brands were bought interchangeably and roughly in line with their market shares. Indeed, there are no signs of any sizeable segmentation in the market between brands and private labels. Furthermore, private label buyers do not differ from brand buyers, and the high private label w exists throughout the buying population (see section 5.5 page 168).

Though these explanations could in principle account for the high private label w, we have no evidence to suggest that they do. However, we do have evidence to support the population at risk explanation. This is examined in the following section. First, we outline the problem and explain how limited availability affects the calculation of penetration. Then we show that private label distribution is indeed more limited than that for brands.

In section 5.4, analyses are undertaken which try and account for the high private label purchase rate. These include; re-estimating a population at risk for each private label to determine whether the new penetration is more in line with the original purchase rate; grouping all private labels into a mega-private label which overcomes their limited availability; analyses at the within-store level where buying populations are the same for all items; examining the distribution implications for OBPL; and finally reviewing other research in the area.

5.3 POPULATION AT RISK

Ehrenberg (1988 page 76) summarises the salient points on how the population at risk affects the NBD model. (The underlined parts are particularly relevant for the study of private labels).

'... the wrong definition of the population of consumers is potentially another general factor which can lead to discrepancies. Thus for some products it is not very clear whether the buyer is a household or some specified individual...Furthermore, some segments of the population may not be potential

buyers of the product at all (or hardly at all), such as non-motorists for petrol and motor oil, non-owners of dogs for pet foods, non-smokers for cigarettes, and so on. In other product classes, the never buyers may be less obvious to identify.'

This issue has received some attention from other researchers, but rarely in the context of private labels, and mainly in relation to the NBD model. Research has focussed primarily on the more technical issues (Massy et al 1970 page 336, Chatfield, Ehrenberg and Goodhardt 1966, Morrison 1969, Ehrenberg 1970, Morrison and Schmittlein 1988) and to a lesser extent on store location (Wrigley and Dunn 1984a and 1984b).

5.3a The Problem

Throughout the analyses in chapter 4, much emphasis has been placed on the importance of the sales equation. One of its main components is penetration which is calculated as:

$$b\% = \frac{\text{number of households buying at least once in a given time period}}{\text{the total sample population of potential buyers}} * 100$$

Penetration is input directly into the NBD, and forms a component of market share which is input into the Dirichlet model. From the base period input, the model is calibrated and theoretical predictions are generated. It is therefore important that penetration is correctly specified, and is on the same basis for all items in the product field. However, there is a difference in the specification of penetration for brands and private labels.

In these analyses, the potential buying population is the AGB continuous consumer panel which is a representative sample of households in a particular region. The sample is representative in terms of demographic and socio-economic variables. These include social class, age of housewife, family size, presence of children and ITV viewing status. Panelists are selected within post-code areas with their numbers proportional to the size of the population in that particular region (for full sample details see AGB Reference Manual 1985). No account is taken of proximity to specific chains, although research has shown that distance and driving time are the main factors influencing store choice which is particularly relevant in a study of private labels (Herman and Beik 1969, Uncles 1985 chapter 2).

If, for example, there are no Sainsbury stores in the locality, those living in the area will have no access to the chain unless they are willing to travel outside the area. In practice some people have access to the majority of chains, whilst others are considered out of reach or too far away to visit regularly. Even if an individual has access to all store chains, he may choose not to visit one and so fail to be part of that stores population at risk in reality. These differences mean that the opportunity to buy the Sainsbury private label is less than for the average brand.

To a lesser degree, the problem of limited availability also applies to brands. Though the majority of larger brands are available in most outlets, many of the smaller ones are not. However, even those brands with the smallest market shares tend to be more available than the largest private label, as we show in section 5.3b (page 141).

As a result, there is less opportunity to buy a specific private label than the average brand. This disadvantage has direct repercussions on the calculation of penetration because the relevant population at risk varies for all items in each product field, and the difference is especially noticeable between brands and private labels. This causes problems in the calculation of observed penetration because figures are drawn from the same sample of potential buyers for all items which does not reflect their availability. These penetration figures are then used as input in the base period which partially calibrates the model. This then has repercussions on all other aspects of buyer behaviour. The effect of limited availability on the calculation of penetration is illustrated below.

Figure 5.1 : Penetration Calculations

Population of buyers = 10	Population of Buyers = 10
Robinsons	Sainsbury
Availability	Availability
9	5

90% of the population have access to the Robinsons brand of Fruit Squash and 50% to the Sainsbury private label in a given time period. If four people purchase Robinsons and four purchase the Sainsbury private label, their penetrations calculated in the usual manner are;

$$\begin{aligned} \text{Robinsons} &= 4 / 10 = 40\% \\ \text{Sainsbury} &= 4 / 10 = 40\% \end{aligned}$$

However, when we allow for the population at risk in accordance with their relative availability, the private label penetration differs substantially;

$$\begin{aligned} \text{Robinsons} &= 4 / 9 = 44\% \\ \text{Sainsbury} &= 4 / 5 = 80\% \end{aligned}$$

By adjusting the population at risk in accordance with availability, the estimated penetration for Sainsbury rises from 40% to 80%. The implication here is that the penetration of the Sainsbury private label is held down because it is only available to a segment of the market. The seemingly high average private label purchase frequency (Table 4.2 page x), should in principle be more in line with the revised higher penetration figure. This logic derives from the fact that penetration and purchase frequency are positively related by the Double Jeopardy pattern, as expressed by the $[w (1-b)]$ equation (section 4.2a page 92) which is theoretically constant for all items in a product field in a given time period. So b cannot be deemed high or low without considering its purchase frequency and vice-versa.

Availability is used as a means of estimating the relevant population at risk. However, this does not take into account the individual who chooses not to visit a certain chain despite having access, nor does it overcome differences in the opportunity to buy. ie when an individual is in Sainsbury, she cannot buy the Tesco private label. Availability may therefore overstate the relevant population at risk. As a result of this limitation and others which we discuss later, three estimates are derived for the population at risk. These provide sufficient variation to allow for limitations in the measurement technique adopted.

In summary, limited availability affects the calculation of observed penetration which has repercussions on other observed and theoretical buyer behaviour measures. The observed values then consistently differ from the theoretical estimates and this causes the apparently high private label purchase rate.

To test this hypothesis, we first examine how private label availability differs from brands.

5.3b Differences In The Availability Of Private Labels And Brands

In order to assess private label availability, distribution is used as a proxy. However distribution is not the same as availability because an item can be 100% available without being distributed in all outlets. This occurs because there are trading area overlaps between stores, and most people tend to shop in more than one store for their grocery purchases (Kau and Ehrenberg 1984, Uncles and Ehrenberg 1988, Wrigley and Dunn 1984b, Kau 1981). Therefore, the opportunity to buy a given item is often greater than its distribution figure implies which compensates for the fact that availability overstates the population at risk somewhat. Nevertheless, bearing these limitations in mind, distribution provides a possible proxy for availability.

Various measures of distribution are available. Indeed market research organisations, eg Nielsen and Retail Audits, collect store distribution information, but are unable to make this available on a named chain basis for reasons of confidentiality. Only distribution through various aggregates such as the largest multiples are available. This is not store specific and so can not be used in the analysis where an estimate of each retail chains distribution is needed. The three main measures of distribution used by Nielsen are:

- 1) **Shop (Numerical) Distribution** - this is the proportion of stores, of a particular type, handling the item at some time during the audit period.
- 2) **Sterling (All Commodity Volume) Weighted Distribution** - this is the proportion of total annual grocery turnover accounted for by shops handling the particular item in the audit period.
- 3) **Product Field Weighted Distribution (Product Class Distribution)** - the proportion of product field turnover accounted for by shops handling that item.

Shop distribution is the simplest measure but is inappropriate as a proxy for availability because it takes no account of differences in store size. For example, Sainsbury's shop distribution will be smaller as a proportion of the total number of grocers in the region, though it may account for a larger share of the items sales. This measure under-estimates the distribution for larger stores and over-estimates it for smaller ones. Product field weighted distribution is also inappropriate because it only considers one product field at

a time which is too restrictive as a measure of access to the store generally.

Sterling weighted distribution is the closest proxy to a measure of access for a given store. It reflects distribution in all product fields in relation to store turnover. It therefore provides a good proxy to store access generally. However, this measure is not available on a named store basis for reasons of confidentiality so a distribution index based on the same logic is derived from our panel data.

For this index, distribution is measured as the number of chains where the item is sold, multiplied by the market shares (based on share of 73 product fields covered by AGB see Appendix 8) of all the stores in which the item is stocked. Details of this distribution index are provided below.

A Distribution Index

An index of distribution was calculated for each brand and private label of Fruit Squash and Fabric Conditioner in London and Lancashire. Fruit Squash (London) is shown for illustration purposes (Table 5.1), others are shown in summary form, with details in Appendix 6.

A 48 week time period is used to calculate the distribution index because this gives a more accurate indication of which stores stock which items. However, even in a 24 week time period, the distribution index is similar to the 48 week index (Appendix 7). The main difference between the two time periods is that items with smaller market shares are less likely to be bought in all store chains in which they are stocked. Therefore, given our intention is to show distribution differences, a longer time period is used to reflect the distribution of each item and this also matches our predominant analysis period of 48 weeks.

Various assumptions are made in calculating the distribution index. For example, if a panelist buys an item from a store in the 48 weeks under analysis, we assume it is available throughout the 48 week period, though in reality this may not be so. Stock-outs and delistings mean that sometimes items are not always available. However, stock-outs tend to occur at individual store sites rather than affecting all stores in a chain. This means they are unlikely to affect the validity of the distribution index. Delistings mostly occur with minor brands which are grouped in the "others" category. This would only

affect the index if all minor brands were simultaneously delisted, which is unlikely to happen in practice.

It is also assumed that if a store chain stocks an item it will be bought at least once in 48 weeks by someone on the panel. This is a realistic assumption for all but the smallest items. For example, there are only 12 Wells buyers in total in the 48 week period. Given this, it may be possible for a store to stock Wells but no panelist is recorded as buying it. The distribution index can understate the availability of smaller items, though this is reduced somewhat by using a long time period.

Nevertheless, bearing these points in mind, the index can still provide a possible proxy for distribution.

Table 5.1 : A Distribution Index For Fruit Squash (London 48 weeks)

Items	Ro	Ki	RB	OB	R	Qu	St	Vi	Sq	Go	Co	We	Su	PL	MS
Stores :															
Sainsbury	*	*	*	*	*	*	*	*	*	*				*	40.0
Tesco	*	*	*	*	*	*	*	*			*			*	16.1
Coop	*	*	*	*	*	*					*			*	7.4
Waitrose	*	*	*	*		*	*		*					*	6.1
Safeway	*	*	*	*	*	*	*	*	*		*	*		*	5.6
Dee	*	*	*	*		*		*		*	*	*		*	5.0
Others	*	*	*	*	*	*	*	*	*		*	*	*	*	4.8
Internatnl	*	*	*	*	*	*					*			*	3.0
Asda	*	*	*	*	*	*			*					*	3.0
Presto	*	*	*	*	*	*		*						*	2.5
M&S														*	2.5
Fine Fare	*	*		*		*			*			*		*	2.0
Boots	*		*	*		*								*	1.0
Spar	*	*	*		*	*		*						*	1.0
Index	98	97	96	97	83	98	73	75	61	45	42	17	5	100	100

* Key : Ro Robinsons; Ki Kia Ora; RB Robinsons Barley; OB Other Brands; R Roses; Qu Quosh; St St.Clements; Vi Vimto; Sq Sunquick; Go Gollicrush; Co Corona; We Wells; Su Sunland; PL Private Label; MS Market Share

A * in the body of Table 5.1 means that the item is stocked by that particular chain. Each * is then weighted by the chain's market share. The market share figure is each stores share of trade of 73 TCA product fields for the London region. In the Robinsons (Ro) column for example, each * is multiplied by the corresponding row's market share figure and these are then aggregated to produce the highlighted sum at the bottom of the column. The resulting index for each brand is shown in the final row of Table 5.1.

Private labels are only available in one chain, so their distribution index is the market share for the relevant chain. This is summarised in Table 5.2. On average brands have 68% distribution in comparison to only 8% for private labels. Average brand distribution is over 8 times greater than for the average private label. Even in London where Sainsbury has such a dominant market share of 40%, its private label distribution exceeds only that of Wells and Sunland, with 16% and 5% respectively.

Table 5.2 : Summary Of Brand And Private Label Distribution Index (London 48 weeks)

Brands :		Private Labels :	
Robinsons	98	Sainsbury	40
Quosh	98	Tesco	16
OB	97	Coop	7
Kia Ora	97	Waitrose	6
RB	96	Safeway	6
Roses	83	OBPL	5
Vimto	75	Dee	5
St. Clements	73	Asda	3
Sunquick	61	International	3
Gollicrush	45	Presto	3
Corona	42	Fine Fare	2
Wells	16	Boots	1
Sunland	5	Spar	1
Average	68		8

Distribution indexes were also calculated for Fruit Squash and Fabric Conditioner in London and Lancashire. The same order of difference between brands and private labels occurred in these other data sets. Private label

distribution ranges from 1% to 40%, in comparison to that for brands of 5% to 99% (Table 5.3). Though brand distribution falls to 5% this is only for a couple of brands, the majority have much wider distribution (see Appendix 6 for details).

Table 5.3 : Range Of Distribution Index For Two Product Fields (48 weeks)

	Brands		Private Labels	
	London	Lancs.	London	Lancs.
Squash	5-98	26-99	1-40	1-14
Fabric Cond.	6-95	24-95	2-40	1-14

Therefore, private labels do have a significant distribution disadvantage in comparison to brands. We now move on to estimating a more appropriate population at risk for each store chain. However, identifying a more appropriate population at risk is not easy, as Ehrenberg suggests above (page 137). In some product fields such as cigarettes, the population is easier to identify, assuming data is available on those who smoke. The problem is more difficult with private labels as we discuss below.

5.4 ACCOUNTING FOR THE HIGH PRIVATE LABEL PURCHASE FREQUENCY

Here we estimate a more appropriate population at risk for each private label so as to try and account for the high private label purchase frequency. Then analyses which adjust for brand and private label availability are shown. Their results support the finding that fitting the model to those who have access, ie the relevant population at risk, largely accounts for the private label discrepancy.

5.4a Estimating A More Relevant Population At Risk

The population at risk for each store is defined in this thesis as encompassing those panelists who have access to the store, whether or not they buy or intend to buy an item from it in a given time period (Figure 5.2). The population at risk we estimate is the shaded part of figure 5.2. This is only

part of the box, the total of which equates to the population at risk without taking private label limited availability into account. The total box therefore reflects the population from which penetration is usually calculated.

Figure 5.2 : Definition Of The Population At Risk

Population At Risk		
With access to the store		
Access & buy	Access & do not buy in the analysis period A	Access and would never buy B
Without access to store		
Would buy if could	Would never buy	

The Sainsbury population at risk will differ in both its size and composition to the Tesco population at risk. Some individuals will be in both, others in one, and some in neither. Though the population at risk may seem quite simple to measure intuitively, this is not so, as we explain below. Estimates are not perfect, but they provide a sound base for testing the idea that limited availability is the likely reason for the high private label purchase frequency.

There are a variety of methods which could have been use to estimate the population at risk. We need to estimate the number of people in say, London with access to the Sainsbury chain. However, such as trade or catchment area methods from geographical research are either not appropriate or data requirements make their use impractical for our purposes (Applebaum 1966, Berry et al 1958, Converse 1949). The method adopted has the advantage of using existing data and it provides a good empirical estimate of the actual buying population for each store chain.

However, there are two main problems in measuring the population at risk (as defined in the thesis) for each store chain.

It is difficult to identify whether or not an individual is in the population at

risk. This is because whilst all those who purchase in a given time period are part of the population at risk, so are some of those who do not buy.

Purchase incidence is assumed to be stochastic, so even heavy buyers may fail to come into the market on occasion. So the non-buying group with access will comprise two categories: those who happen not to buy in the analysis period, but are part of the population at risk (A); and those who have never bought and will not do so even though they are not part of the population at risk (B). For example, those with access to many stores, but who choose not to buy at Sainsbury, fall into the latter category for the Sainsbury population at risk. The distinction between these two categories can not be measured using panel data, nor do we know what proportion of non-buyers should fall in each category.

It is also difficult to measure the availability of a specific private label. Even if everyone has equal access to all stores, and brands are uniformly available in all stores, the private label would still be at a disadvantage as compared to the average brand. This is because when an individual is in Sainsbury, she can buy any brand in stock or the Sainsbury private label, but not the Tesco private label on that purchase occasion. Therefore, the opportunity to buy any specific private label is less than for the average brand, and even this varies by private label. So it is not simply a matter of access, but also of opportunity to purchase.

In practice these problems are further compounded by the fact that individual store chains are not uniformly available. Some people have access to certain stores and not others, and this will vary by person and degree of accessibility. Some people will choose only to shop at certain stores despite having access to more. Furthermore, brands are not distributed uniformly in all chains; brand leaders have near complete distribution but smaller brands have fewer listings.

The measurement problems outlined above need to be taken into consideration in interpreting the analysis results. Identifying whether or not individuals are part of the population at risk is a problem that applies to private labels and to a lesser extent, brands. In order to estimate the population at risk so that it includes those who did not buy in the analysis period, but who are still part of the population at risk, and make some allowances for differences in the opportunity to buy, a conservative and a more liberal estimate is made.

Intuitively we believe that the relevant population at risk lies somewhere within this range.

Three estimates of the population at risk are made, two empirical and one theoretical. This strengthens the validity of the results, and enables us to allow for some of the problems identified above. It must be stressed that the objective of these estimates is not to provide a definitive population at risk for each store chain. Rather, that three empirical estimates support the idea that private labels are indeed at a disadvantage because of their distribution in comparison to brands.

First a conservative estimate of the buying population is made. This includes those who bought any Fruit Squash from a given store chain in 48 weeks. If an individual purchases Robinsons from Sainsbury for example, they are part of the Sainsbury population at risk. Secondly, a more liberal estimate is used. This comprises those who bought from a given store chain any item in any of the 73 packaged grocery fields covered by TCA in the 48 week period.

These two estimates are used because research has already shown that the population at risk will include some non-buyers in the time period under study (Chatfield et al 1966, Massy et al 1970). The stochastic nature of the model means that even those who frequently visit Sainsbury stores, may not do so in the analysis period, yet they are still part of the population at risk. Therefore, to confine the estimated population at risk to just Squash buyers, would almost certainly omit those who visit the store for other than Fruit Squash, and those who failed to buy Squash at Sainsbury in the analysis period. Purchases of 73 product fields are considered because this captures a wider population of potential buyers.

Then a theoretical Dirichlet estimate for penetration is made from which a more relevant population at risk can be derived. There are two conditions which need to be satisfied for this to be an appropriate benchmark. The model specification should reflect a market structure which is a) based on an equivalent population at risk for all items concerned and b) one that reflects the absolute number of choices available in the product field under study.

This means that private label market shares cannot be used as input because they introduce bias into the model estimates. This is because the main

structural Dirichlet parameter "S" (Note 2), is on average lower for private labels than for brands even after allowing for market share differences (Appendix 9). Reasons for this are provided later in the section. So using private labels as input reduces the product field S value and alters the theoretical estimates from those in a market where all items have an equivalent population at risk. However, private labels can not simply be excluded from the model because the absolute number of choices available to the consumer needs to be maintained otherwise this too reduces the S parameter.

A theoretical estimate which satisfies both these conditions is obtained by calibrating the model based on brand information only so that population at risk effects are minimised. More details of this technique are given prior to the analysis (page 153).

The two empirical estimates are then compared with the theoretical one. The exact population at risk is not known, but should lie somewhere between the two empirical estimates. 48 week time periods are used because they provide more data with which to estimate the various populations at risk. However, findings from 24 week analyses also support the general findings.

We now calculate the three population at risk estimates for each store chain. These analyses have been undertaken for 48 weeks for Fruit Squash and Fabric Conditioner in London, but Fruit Squash is shown for illustration purposes.

A Conservative Estimate - Fruit Squash (London) Buyers

For each store the proportion of our sample who bought any item of Fruit Squash in London at that chain is determined. When a buyer makes a purchase from the chain, this indicates that she certainly had access to it (Table 5.4).

Note 2 : "S" is one of the main structural parameters of the Dirichlet model. It reflects consumer diversity or the extent of item switching in the product field.

**Table 5.4 : Penetration of Fruit Squash Buyers
By Store Chain (London 48 weeks)**

Continuous Reporters = 650

	Penetration b%	Buyers
Sainsbury	35.2	229
Other	34.6	225
Tesco	16.9	110
Coop	11.2	73
Safeway	7.9	51
Waitrose	7.1	46
Presto	6.5	42
International	5.4	35
Boots	4.0	26
Asda	3.1	20
Dee	3.1	20
Fine Fare	2.5	16
Spar	2.2	14
M&S	1.9	12
Average	10.0	66

In 48 weeks 35% of the standard population has such access to Sainsburys. So the relevant population at risk for this store is 229 buyers (ie 35% of 650 = 229 buyers). This is our conservative estimate of the population at risk for that particular chain.

In principle the same logic also applies to brands which also vary widely in their availability. However, they still have 8 times the distribution of the average private label (Table 5.2 page 144). Only the smallest brands had a lower distribution measure than the largest private label. Nevertheless, the same population at risk estimate is made for brands by way of comparison.

Table 5.5 figures are obtained by summing the number of buyers with access to each store where the brand is listed. There is no double counting because households who visit a specific chain more than once in the analysis period are only counted once. On average 397 households have access to brands, as compared to an average of 66 households for private labels. Therefore, in this sense brand availability on the whole greatly exceeds that for specific private labels (Table 5.5).

**Table 5.5 : Brand Buyers For Fruit Squash
(London 48 weeks)**

Brand	Buyers
Robinsons	461
Quosh	454
RB	459
OB	458
Kia Ora	454
Roses	441
Vimto	418
St. Clemens	419
Sunquick	397
Corona	310
Wells	270
Sunland	225
Average	397

The population at risk for Corona is 310 buyers which is low for a brand and more in line with that for the larger private labels such as the Sainsbury private label with 229 buyers. Corona is the only itemised brand whose population at risk is similar in size to that for a private label. Other small brands are aggregated into the OBPL category for buyer behaviour analyses. Therefore, Corona provides an interesting comparison between a brand and private label with limited availability. This point is discussed in more detail in section 5.4b (page 163).

Though only Fruit Squash (London) is shown here, similar results are found for Fabric Conditioner (London). We now move on to a more liberal estimate of the population at risk.

A More Liberal Estimate - Buyers Of 73 TCA Product Fields

For each store chain the proportion of our sample buying any item from 73 TCA (AGB) product fields at that chain is determined. These 73 fields include a selection of standard packaged grocery products believed to be representative of the consumers shopping basket. If the buyer bought any item from a particular store in a 48 week period, this indicates she had access to the chain.

In 48 weeks 88% of our population has access to Sainsbury (Table 5.6). So the population at risk estimate for this store is 574 buyers ($650 * 0.883$). This is a more liberal estimate of the population at risk for that particular chain and so is larger than the Conservative estimate of 229 buyers (Table 5.4). On average, 234 buyers had access to the average private label as compared to an average of 66 from the conservative estimate (Table 5.4).

**Table 5.6 : Penetration of 73 TCA Fields Buyers
By Store Chain (48 weeks)**

Continuous Reporters = 650

	Penetration b%	Buyers
Sainsbury	88	574
Tesco	69	445
Coop	65	423
Waitrose	33	217
Asda	29	189
Others	28	182
Presto	23	146
Safeway	15	98
FFare	5	29
Dee	5	33
Average	36	234

In principle, the reasons for making a liberal estimate of the population at risk for private labels also applies to brands. Some people who have access to a brand, did not buy a brand of Fruit Squash in the analysis period. Unfortunately data is not available for estimating a liberal population at risk for each brand because data was only provided in a tabulated format. However, an average of nearly 400 buyers had access to Fruit Squash brands in our conservative estimate (Table 5.5), so the liberal estimate must be in excess of this. Therefore the liberal population at risk for the average brand (over 400 buyers) could be more than double that for the average private label (234 buyers).

We now derive a theoretical estimate for the population at risk with which to

compare the two empirical estimates.

A Theoretical Dirichlet Estimate

The objective here is to use the Dirichlet model to predict an appropriate penetration level given a purchase frequency. This is explained in more detail below. However, the Dirichlet model needs to be calibrated so that population at risk effects are minimised.

This means that private label market shares can not be used as input because their values of the components of the sales equation (b and w) differ from that for brands (Table 4.3 page 89). This introduces bias into the model because their high purchase rate in relation to penetration, lowers the S value (see Note 2 page 149). Private label S values are lower than brands because the high buying rate means there is less opportunity for private label buyers to switch among other items in the product field. Furthermore the absolute number of items in the product field must be maintained because a reduction here also reduces the degree of switching and therefore the S value.

Estimates which satisfy both these conditions are achieved by calibrating a model with brand information only as input, but without reducing the absolute number of items available in the product field. Even here there are likely to be some population at risk effects because some brands also have low distribution levels. Another way to achieve this would have been to specify the model using only brand information. However, results from this method differ little from the method explained in the previous paragraph so either method could have been adopted.

The Dirichlet model is estimated by fitting the model to the whole product field and then changing the S value prior to the theoretical predictions being calculated so that the theoreticals are in line with the brand values. The model fit is closest to the average brand when S equals 3 (S values were varied from 1.5 to 3.5).

Model estimates for $S = 3$ are shown below with the standard model (STD) for comparison (Table 5.7). The standard model is based on the same calibration as was used in chapter 4 (Table 4.2 page 88). By fitting the model to brands, the private label deviation is accentuated; on average they are bought by 20% (26%) of buyers, 5.3 (3.7) times. So the private label fit is worse than for the

standard model where 20% (22%) bought 5.3 (4.5) times. This is because the deviations for brands and private labels are in opposite directions, so any improvement in one will be to the detriment of the other.

Table 5.7 : Dirichlet Estimates For Fruit Squash Where S Parameter = 3 (London 48 weeks)

	b%		std	w		std
	O	T		O	T	
Brands						
Robinsons	29 (29)	(24)	3.8	(3.7)	(4.5)	
OB	22 (19)	(15)	2.8	(3.4)	(4.1)	
Quosh	20 (22)	(18)	3.7	(3.3)	(4.2)	
Kia-Ora	15 (14)	(11)	2.8	(3.1)	(4.2)	
RB	10 (11)	(9)	3.3	(3.0)	(3.9)	
Corona	3 (5)	(4)	4.0	(2.9)	(3.7)	
Average	17 (17)	(14)	3.4	(3.4)	(4.1)	
Private Labels						
Sainsbury	30 (43)	(38)	6.6	(4.7)	(5.3)	
OBPL	29 (30)	(25)	3.9	(3.8)	(4.5)	
Tesco	11 (18)	(15)	5.4	(3.3)	(4.1)	
Coop	8 (13)	(10)	5.2	(3.1)	(3.9)	
Average	20 (26)	(22)	5.3	(3.7)	(4.5)	

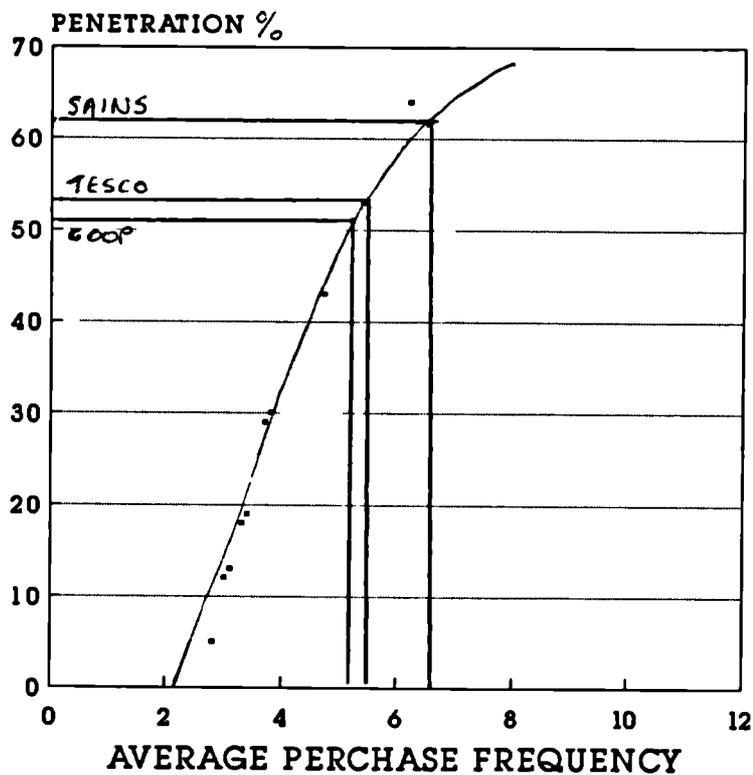
Note : S value for standard model = 1.6

The new model specification is therefore based almost entirely on brand information. As such the estimates show the relationship between penetration and average purchase frequency as would occur with only limited population at risk effects.

The theoretical estimates from this new model for b and w are plotted (Graph 5.1). This is because we know there is a relationship between b and w as described by the Double Jeopardy pattern, so we can predict one from the other. For example, 29 and 3.7, 19 and 3.4 etc for each brand and private label in the product field. The resulting curve illustrates the relationship between b and w in the Fruit Squash (London) market when items have a near equivalent population at risk.

Using this graph we can predict the level of penetration which should accompany a given purchase rate. We assume that the purchase frequencies are "correct", the adjustment for population at risk being catered for in the b. For example, the observed Sainsbury private label purchase frequency is 6.6 (Table 5.7) and reading from the graph this yields a penetration of 62%; for the Tesco private label corresponding figures are 5.4 and a penetration of 52%; for the Coop private label, 5.2 and 50%.

Graph 5.1 : Theoretical Estimate Of The Population At Risk For Fruit Squash (London 48 weeks)



From these re-estimated penetration figures, we can derive the theoretical estimate of the population at risk. For example, for the Sainsbury private label, 62% of 650 buyers is 404. 404 buyers have access to it which is well below the 650 buyers in the sample of continuous reporters.

Theoretical estimates are calculated in the same way for the other private labels of interest (Table 5.8). (OBPL has been excluded because this is an amalgamation of individual private labels and so differs in respect of its distribution. It is discussed more fully in section 5.4b). The new theoretical penetration figures which take account of the population at risk are higher than those observed originally. For example, Tesco penetration rises from 11% to 52% and Coop from 8% to 50%. This occurs because the actual number of buyers for each private label is taken as a proportion of a smaller group of potential buyers which only includes those who have access to the store.

Table 5.8 : Private Label Theoretical Penetration Estimate (48 weeks)

	w	0 b%	(T) b%	Population At Risk
Sainsbury	6.6	30	62	403
Tesco	5.4	11	52	338
Coop	5.2	8	50	323

Comparing The Three Estimates

We now have three estimates of the population at risk for Fruit Squash (London) for each store chain. Absolute numbers of buyers are shown because these are the new equivalents to the original sample of 650 continuous reporters (Table 5.9).

Table 5.9 : Three Estimates Of The Population At Risk (48 weeks)

Store	Original b buyers		Conservative b buyers		Liberal b buyers		Theoretical b buyers	
Sainsbury	30	195	35	229	88	574	62	403
Tesco	11	72	17	110	68	445	52	338
Coop	8	52	11	73	65	423	50	323

Table 5.9 shows that all three estimates confirm that the population at risk for private labels is indeed below the 650 used throughout chapter 4 analyses. In fact the conservative estimate for Coop is only 11% (73 of 650) of the original sample of 650 continuous reporters. This means that private label penetration figures are indeed under-estimated.

All three estimates indicate that Sainsbury has the largest population at risk, followed by Tesco and Coop. The order of size remains the same irrespective of which estimate is used, though the extent of the difference reduces as the size of the population at risk increases. This is because it is more likely that an individual will fail to buy Fruit Squash from a store chain than not buy something from 73 product fields.

In practice we do not know where the true population at risk lies in this spectrum. Intuitively though, it is likely to be somewhere between the two empirical estimates.

The theoretical estimate is essentially saying that if private labels behaved like a brand, their population at risk would on average be closer to the more liberal estimate.

We can now use these revised penetration estimates to determine the population at risk which would imply the high w value for private labels. This is achieved by using the $[w_0/(1-b)]$ equation which was discussed in more detail in section 4.2a (page 91). This provides a means of examining the direct relationship between b and w , without the added complexities of the Dirichlet model. In any given product field, b and w are inextricably linked and within narrow limits there tends to be only one combination to give a certain sales level.

The $w_0/(1-b)$ equation is used to predict a new w estimate from the revised penetration figures in Table 5.9. However, rather than using the average $w(1-b)$ for the whole product field for Fruit Squash (London), only brands are used to estimate w_0 . This is because population at risk effects are minimal for brands. The average $w(1-b)$ for brands is 2.8 (Table 4.5 page 92). Each of the three penetration estimates in Table 5.8 is input to the $w_0/(1-b)$ model to provide estimates for w (Table 5.10).

Table 5.10 : $w_o/(1-b)$ where $w_o=2.83$ (48 weeks)

Store	Original		C		L		T		Avge C+L		Avge C+L+T	
	b	w	b	w	b	w	b	w	b	w	b	w
Sains	30	6.6	35	4.3	88	23.3	62	7.4	62	7.4	62	7.4
Tesco	11	5.4	17	3.4	69	9.1	52	5.8	43	4.9	46	5.2
Coop	8	5.2	11	3.1	65	8.0	50	5.6	38	4.5	42	4.9

Note : C - Conservative, L - Liberal, and T - Theoretical estimates.

We find that the original purchase frequencies lie between the conservative and liberal estimates and are slightly below the theoretical one. The purchase frequencies are in fact closest to the average of all three estimates; Sainsbury 6.6 (7.4), Tesco 5.4 (5.2) and Coop 5.2 (4.9). This intuitively makes sense given that the population at risk should include a proportion of the non-buying population, those who fail to buy for whatever reason.

The Sainsbury liberal estimate (23.3) is high because of the very high penetration figure. The $[w_o/(1-b)]$ equation is less accurate for very small or large brands.

By solving the $[w_o/(1-b)]$ equation for b, we can calculate the penetration which equates to the observed w.

Sainsbury	$2.83/(1-b) = 6.6$	therefore b=57%
Tesco	$2.83/(1-b) = 5.4$	therefore b=48%
Coop	$2.82/(1-b) = 5.2$	therefore b=46%

These show that the average of the three estimates is closest to these penetration figures. Tesco and Coop are slightly above the estimate with Sainsbury a little below.

Summary

These analyses do not provide a definitive answer to the exact size of each store's population at risk. This is not possible due to the stochastic nature of purchase incidence. However, the results provide collaborative evidence for the explanation because each estimate shows that the population at risk is indeed

over-estimated in the usual method of calculating buyer behaviour statistics.

This means that private labels have an apparently high purchase rate because of their limited availability rather than implying any heightened loyalty to them.

Therefore, rather than private labels having a high purchase frequency, it is in fact more likely to be that their penetration is under-estimated.

The same analysis was also undertaken for London Fabric Conditioner and results supported these conclusions.

The analyses show that the relevant population at risk for private labels is indeed smaller than the 650 continuous reporters from which the original penetration is calculated. When the appropriate population at risk is taken into consideration, private label penetrations rise and do so in a manner which largely accommodates for the somewhat high purchase frequency.

These findings have been generalised to Fabric Conditioner (London) also. Lancashire has not been examined because no data was made available for purchasing the 73 product fields in the Lancashire region which is needed for the more liberal estimate and sample sizes in this region are too small for population at risk analyses.

The population at risk explanation is explored further but approached in a different manner. We compare brand and private label buying patterns where they have an equal population at risk. This overcomes the problem of private label limited availability and we find that both their purchase rates and penetrations are closely predicted by the Dirichlet model. We examine private labels in the aggregate, by purchasing within store chains, and look at OBPL and other relevant research.

5.4b Supporting Analyses

First, individual private labels are aggregated to form a mega-private label which overcomes their limited availability. Then analyses within the store chain are undertaken where the populations at risk for brands and private labels are equal being equivalent to the store chain's clientele. The OBPL category is then discussed because its deviant nature in Chapter 4 (Tables 4.1 and 4.2) is a

result of it having wider availability than the average private label. Finally, other research in the area is reviewed.

Analyses have also been generalised to Fabric Conditioner in London and Lancashire, and their results are shown below.

A Mega-Private Label

Aggregating individual private labels into one group (ie mega-private label) compensates for the effects of their limited availability. This is especially so in London where the majority of chains offer private labels. Therefore, the opportunity to buy any private label is similar to that for any brand as they are available in nearly all stores.

This summation is theoretically feasible because the Dirichlet model possesses an important "additivity" property;

" An important property of the model is that any 2 brands j and kcan be combined into a super-brand....Nothing else in the specification of the Dirichlet model is affected (Wilks 1962). This feature is not common to other models. " (Goodhardt et al 1984)

When private labels are aggregated, their average purchase frequencies largely fall in line with the rest of the product field. For example, with Fruit Squash (London), 53% (56%) of individuals buy private labels and do so 7.8 (7.4) times. Though the purchase rate is a little higher here, it is not a general finding (Table 5.11). Indeed in the other three data sets, the average private label purchase frequency is lower than predicted.

Table 5.11 : Dirichlet Estimates For A Mega-Private Label (48 weeks)

	O	b T	O	w T		O	b T	O	w T
Fruit Squash: London					Lancashire				
Totpl	53	(56)	7.6	(7.4)	Totpl	44	(41)	5.6	(6.0)
Rob	29	(24)	3.8	(4.6)	OB	37	(31)	4.4	(5.3)
OB	22	(15)	2.8	(4.2)	Quosh	32	(25)	3.9	(5.0)
Quo	20	(17)	3.7	(4.3)	Rob	31	(32)	5.7	(5.4)
Kia	15	(11)	2.8	(4.1)	Kia	27	(25)	4.7	(5.0)
RB	1	(9)	3.3	(4.1)	Vimto	25	(36)	8.1	(5.6)
Cor	3	(4)	4.0	(3.9)	RB	8	(8)	4.2	(4.3)
Wells	2	(2)	2.3	(3.8)					
Average	20	(17)	3.8	(4.5)	Average	29	(28)	5.2	(5.3)
Fabric Conditioner: London					Lancashire				
Comfort	35	(35)	4.2	(4.2)	Comfort	38	(37)	5.0	(5.1)
Totpl	30	(30)	3.0	(4.0)	Totpl	23	(21)	3.6	(3.8)
Lenor	25	(27)	4.2	(3.9)	Lenor	18	(17)	3.1	(3.3)
Softlan	7	(6)	2.9	(3.2)	OB	17	(15)	2.8	(3.2)
OB	5	(3)	2.0	(3.2)	Softlan	11	(9)	3.6	(4.3)
Form 77	4	(4)	1.8	(3.2)	S&G	7	(10)	1.9	(2.7)
Average	18	(18)	3.2	(3.6)	Average	19	(18)	3.3	(3.7)

Note : average 24 week base used in fitting the Dirichlet model.

Therefore, when private labels are aggregated into a mega-private label, the private label purchase frequency discrepancy is no longer systematically evident. This means that once we make allowances for their limited availability and consequently different populations at risk, their purchase rate falls largely in line with the predicted level. Private labels do not seem to attract a higher incidence of repeat-buying loyalty in this respect.

This result generalises. The same findings occur for Automatic Washing Powder, Tea Bags and Instant Coffee (Lamb and Goodhardt 1988). Studies on US data were also undertaken where private labels were aggregated to overcome problems of small sample sizes. It was found that private labels followed the

same buying patterns as brands, and the high private label w was not present (Uncles and Ellis 1989a and 1989b Appendices 10 and 11).

These results support the population at risk explanation rather than there being any heightened repeat buying loyalty for private labels. Once availability is similar for all items, the private label discrepancy is no longer consistently present.

Purchasing within store chains is now examined.

Purchasing Within Store Chains

Examining brand and private label purchasing within store chains also reduces their availability to a common base. The population at risk is equivalent to the clientele for that store and so is the same for brands and private labels. Purchasing within Sainsbury and Tesco stores only is detailed below, but within store purchasing is examined in more detail in chapter 6.

For purchasing within stores, we find that private label penetration and purchase frequency is much in line with the model predictions (Table 5.12). For example, in a 48 week period, the Sainsbury private label is bought 6.5 (6.8) times by 30% (29%) of households. The same results were found in other stores for Fruit Squash and Fabric Conditioner in London and Lancashire (section 6.3a page 179).

Table 5.12 : Penetration And Average Purchase Frequency Within Store Chains For Fruit Squash (London 48 weeks)

Sainsbury			Tesco		
	b	w		b	w
Sainsbury pl	30 (29)	6.5 (6.8)	Tesco pl	11 (12)	5.4 (5.2)
Robinsons	10 (10)	4.0 (4.0)	Robinsons	7 (5)	2.8 (3.7)
OB	5 (3)	2.3 (3.6)	Quosh	7 (6)	3.0 (4.0)
RB	4 (3)	3.5 (3.6)	OB	2 (1)	2.1 (3.3)
Quosh	1 (1)	1.1 (3.4)	RB	2 (1)	2.8 (3.3)
Avge	9 (8)	3.5 (4.2)		6 (5)	3.3 (3.9)

Note : average 24 week base used in fitting the Dirichlet model.

An interesting finding is that the private label has a tendency to be the within-store "brand leader". This feature is examined in Chapter 6 and developed more in the final discussion chapter.

Once purchasing is examined with reference to a common population at risk, the difference identified in Chapter 4 is no longer consistently present. This lends further support to the population at risk explanation, rather than private labels attracting more repeat-buying loyalty.

OBPL Overcomes Limited Distribution

OBPL is an amalgamation of individual private labels from all non-itemised multiples, supermarkets and voluntary groups. In chapter 4 (Tables 4.1 and 4.2) it was shown that its penetration and purchase frequency did not follow the same patterns as the other private labels. Its penetration was higher, and purchase frequency lower than predicted by the Dirichlet model. This occurs consistently in all five product fields studied (Table 5.13). On average 17% (14%) of buyers bought OBPL and did so 4.5 (5.5) times. The discrepancy is therefore of a similar nature to that for the average brand as shown in the bottom line of Table 5.13.

Table 5.13 : OBPL Penetration And Average Purchase Frequency Across Five Product Fields (48 weeks)

Product Field	Region	b		w	
		O	T	O	T
Fruit Squash	Lon	29	(25)	3.9	(4.5)
	Lan	24	(22)	4.3	(4.7)
Fab. Cond	Lon	11	(9)	2.8	(3.2)
	Lan	8	(5)	2.2	(3.3)
Beans	Lon	24	(14)	7.0	(11.8)
	Lan	13	(11)	8.8	(10.1)
Coffee	Lon	20	(18)	4.1	(4.7)
	Lan	18	(17)	4.8	(5.2)
Wash. Liquid	Lon	14	(12)	3.4	(3.7)
	Lan	7	(5)	3.2	(4.1)
Average Avge Brand		17	(14)	4.5	(5.5)
		17	(15)	4.8	(5.6)

These results suggest that once individual private labels are aggregated so as to overcome to some extent their limited distribution, they are bought much like brands. The discrepancies in b and w which were identified in chapter 4 are no longer present in Table 5.13. It is also important to note that smaller retail outlets are most commonly used for "top-up" purchasing and so are visited by many people who buy infrequently. These results are likely to be due to a combination of such factors.

Another deviation identified in chapter 4 was for Corona (Tables 4.2 and 4.3). Its penetration was below, and its purchase frequency above model predictions. This is a small brand with similar distribution to the Sainsbury private label (Tables 5.4 and 5.5 pages 150 and 151). When distribution is limited, be it for a brand or private label, this results in a high w and low b in comparison to the model predictions. However, we must not draw too many conclusion from Corona because it is such a small brand.

Nevertheless, these results both lend support to the idea that limited availability and a mis-specified population at risk account for much of the discrepancy identified for private labels in chapter 4.

Other Research

There has been some research on population at risk issues (Wrigley and Dunn 1984a, Jeuland 1979). The former focus on store location effects whilst Jeuland refers to private label limited distribution directly. Findings from Chapters 4 and 5 are consistent with their results. These are briefly reviewed below.

Wrigley and Dunn

In a series of papers on stochastic modelling of buyer behaviour, Wrigley and Dunn applied the NBD and Dirichlet models to panel data for individual stores in Cardiff. The population at risk findings reported in this chapter, are analogous to those reported in the first of their papers. Though their analyses relate to store choice and they use the NBD model, the issues raised are similar to those relating to a population at risk mis-specification for private labels. They found that the fit of the NBD could be improved substantially when it was refitted to a locational sub-sample.

When the NBD model was applied to a citywide sample in Cardiff, consistent discrepancies were found between the observed and theoretical measures. Local

stores had a slightly higher purchase frequency than expected, 4.4 (4.2) and 5.7 (5.2). The opposite occurred for central stores (Table 5.14). Though these differences are small, they are consistent. They are also NBD predictions which means they understate any deviations of this nature as compared to Dirichlet estimates. This is because the NBD model takes into account the penetration and purchase frequency of individual stores in calibrating the model.

This deviation occurs because stores in Cardiff have varying degrees of accessibility, which is accentuated by poor public transport facilities. Stores located in the city centre were widely accessible with citywide catchment areas. In contrast, suburban stores served local trade areas. Therefore "to use all 8 survey areas, effectively assuming a citywide catchment area, may produce specification errors." (Wrigley and Dunn 1984a page 642). This is the same type of deviation that was noted in Chapter 4 whereby some stores, and hence their private labels, are much more accessible than others and this difference needs to be taken into consideration.

To overcome the problem, they divided the sample into two subsets to reflect people living in certain catchment areas. The NBD model was then re-fitted on each subset with the result that the consistent discrepancy identified above was no longer present.

Table 5.14 : Penetration And Average Purchase Frequency For Cardiff Stores (48 weeks)

	All Stores Model				Suburban Sub-sample			
	O	b T	O	w T	O	b T	O	w T
Central :								
Tesco	22	(20)	3.1	(3.3)				
Leo	12	(12)	4.5	(4.7)				
Suburban :								
Lipton	10	(11)	4.4	(4.2)	36	(36)	4.4	(4.4)
International	8	(9)	5.7	(5.2)	65	(66)	5.7	(5.7)

When an adjustment is made for the relevant population at risk, the systematic discrepancy is corrected. For example, penetration for Liptons rises from 10% to 36% because a smaller base of potential buyers is used. The theoretical rate

of buying which was systematically higher than when based on the full sample, then falls in line with the observed purchase rates. These results are similar to those in section 5.4 when private label limited availability is taken into consideration.

Overall they conclude;

"The performance of the NBD model, in terms of purchasing at individual suburban stores, shows a marked improvement when the model is recalculated on a local sub-sample which corresponds to, or approximates to, the trade area of the store, and which may also be called the relevant population." (Wrigley and Dunn 1984a page 642)

The way Wrigley and Dunn account for the mis-specified population at risk differs from that used in sections 5.3 and 5.4. They estimate the store's catchment area and select a subsample of people located in the area on which they specify the model. However, in section 5.4, the adjustment is made on the full sample rather than remodelling on a subset. This is because it is easier, no additional data on such as catchment areas is needed and it would be difficult to determine the catchment area for a whole store chain. Also, Wrigley and Dunn use the NBD model (they use the Dirichlet in a later paper), whereas the Dirichlet model is used in section 5.4. The NBD is in fact a more robust test of discrepancies in b and w than the Dirichlet. This is because the NBD takes into account each items b and w directly in calibrating the model.

Despite the different methods adopted for the population at risk adjustment, the results are the same which enhances their reliability.

Jeuland

This study examined the effects of differences in availability on market share. "Until now, no studies of multi-brand choice have explicitly included this feature, yet it is obvious that no buyer is ever exposed on his regular shopping trips to all the brands of the product class. National brands are usually widely distributed, but commonly, one private label is available in only one retail chain" (Jeuland 1979).

He builds a model comprising three components: a micro-multibrand choice model which specifies how preference strength is related to store choice; a

macro-model which describes the heterogeneity of the population with respect to preference strength; and a model of availability.

The distribution component is particularly relevant here. The first two parts of the model relate to the sub-group of buyers to whom the brands are available.

The mathematics of the model specification are not discussed here (See Jeuland 1979 for a full discussion). He conducts an empirical test using French cooking oil. From this test he concludes that the inclusion of a variable to reflect availability makes a significant difference in explaining brand choice behaviour. He found that the brand leader has both the highest preference and availability rating, and so achieves the highest market share. However, private labels had high preference readings, but could not achieve the same market share as the brand leader because of their limited distribution.

This study also shows that availability should be considered in any examination of items which are not similarly available.

These two areas of research are supported by results from the population at risk analysis in the thesis.

Summary

Section 5.4 analyses show that once private label limited availability is taken into account, the high private label buying rate largely falls in line with the model predictions. This means that rather than the private label purchase frequency being high, it is the penetration which is low due to an overstated population of potential buyers. This result has been tested in a variety of ways:

Three independent estimates of a more relevant population at risk were made for each private label for Fruit Squash (London). All three showed that private labels did have a smaller population at risk than the full sample of 650 continuous reporters used in chapter 4 analyses. The new penetration estimates are input into the $w_0/(1-b)$ model to derive estimates of w . The estimate closest to the original observed w was for the population at risk between the conservative and more liberal estimate, and closest to the theoretical one.

Then analyses where brand and private label availability are on a more equal

base were undertaken. Both the mega-private label and within store analyses showed that once availability was taken into account, that private label buying rates were largely in line with model predictions.

Results for OBPL and other research also supported the population at risk argument.

These results are discussed more fully in section 5.6. Though the population at risk analyses largely account for the high private label buying rate, other analyses were undertaken. One such being an investigation of market segmentation, the results of which are now detailed.

5.5 MARKET SEGMENTATION

Much private label research has concentrated on identifying the types of people who buy them on the grounds that somehow they differ from brand buyers. Indeed a recent article suggested that a private label is "targeted at specific consumers and portrays a unique relevant and distinctive personality which is clearly associated with the distributor and is backed by a coherent use of marketing resources." (Chernatony 1988).

If this were the case it would then constitute an identifiable segment for the retailer to target. Various demographic and socio-economic variables have been used to categorise these buyers. Research has shown that "typical" private label buyers are of social class ABC1, between the ages of 16 and 34, and well educated (Livesey and Lennon 1978, Retail Business 1971, JWT 1970, Frank and Boyd 1965).

However, these findings are mostly weak. For example, private label penetration has been found to be higher among ABC1's (19%) as compared to C2DE's (16%). This small difference is typical of results on demographic segments. It is however more likely to reflect a store's clientele rather than anything specifically about private labels. For example, Sainsbury stores have the highest market share in London and their clientele is slightly ABC1 orientated. So any analyses on private label buyers in the London region will comprise a high proportion from the ABC1 social class. Other researchers have found there to be no difference between those who buy brands and those who buy private labels (More details of private label research are provided in the discussion in Chapter, 9).

In order to examine how different demographic segments buy brands and private labels, our data were divided into the following sub-groups:

<u>Sub-Group</u>	<u>Variable</u>
social class	AB, C1, C2, DE
household size	single, 2, 3, 4, 5+
presence of children	with, without
age of housewife	16-25, 26-34, 36-44, 46-64, 66+
housewife working status	full, part-time, not
ITV viewing status	heavy, regular, light, not
light, medium and heavy buyers	1-3, 4-7, 8+
pack sizes	large, medium, small

Data are segmented by each of the above variables within the sub-group and the Dirichlet model fitted on each subset. Buyer behaviour measures are then compared with theoretical Dirichlet estimates. Social class and household size for Fruit Squash (London) are shown in detail for illustration purposes. These two variables are selected because social class is not related to buying frequencies whereas household size is likely to be correlated with the presence of children and so frequency of purchase.

We find that the high private label buying rate occurs across most of the subsets (Table 5.15), rather than being concentrated in just say AB buyers. On average fewer people buy private labels more often than predicted, 14% (17%) buy 4.6 (4.2) times. There are a some discrepancies for households of sizes 2 and 4, where private labels are bought as often or slightly less than expected; 3.2 (3.2) and 4.6 (5.1) times respectively. However these do not generalise further.

Table 5.15 : Penetration And Average Purchase Frequency For The Average Brand And Private Label For Different Social Classes and Household Size (48 weeks)

Social Class

	Brands			Private Labels	
	b	w		b	w
AB	22 (21)	3.6 (4.2)		16 (18)	4.2 (4.1)
C1	19 (16)	3.1 (4.0)		13 (18)	4.8 (4.2)
C2	21 (19)	4.0 (4.6)		14 (16)	4.8 (4.7)
DE	17 (15)	3.0 (3.8)		11 (15)	4.4 (3.9)
Average	20 (18)	3.4 (4.2)		14 (17)	4.6 (4.2)
Household Size					
	Brands			Private Labels	
	b	w		b	w
1	12 (12)	2.1 (2.3)		6 (8)	3.1 (2.3)
2	13 (13)	2.6 (3.2)		10 (11)	3.2 (3.2)
3	25 (22)	3.3 (3.8)		16 (21)	4.6 (3.9)
4	26 (23)	4.3 (5.0)		19 (21)	4.6 (5.1)
5+	29 (24)	4.1 (6.0)		20 (22)	7.6 (6.4)
Average	21 (19)	3.3 (4.1)		14 (17)	4.6 (4.2)

Note : Average 24 week base used in fitting the Dirichlet model.

This result can be generalised across both product fields and regions. For example, social class is shown below for all 4 data sets. The private label w is consistently higher than predicted (Table 5.16).

Table 5.16 : Social Class Average Penetration And Average Purchase Frequency For Two Product Fields (48 weeks)

Product Field	Region	Brands				Private Labels			
		O	b T	O	w T	O	b T	O	w T
Fruit Squash	Lon	20	(18)	3.4	(4.2)	14	(17)	4.6	(4.2)
	Lan	28	(26)	2.9	(3.1)	8	(9)	4.3	(4.1)
Fab. Cond	Lon	10	(11)	2.6	(2.6)	10	(12)	3.2	(2.6)
	Lan	15	(11)	3.4	(4.7)	8	(11)	4.0	(3.0)
Average		18	(16)	3.0	(3.7)	10	(12)	4.0	(3.4)

Note : average 24 week base used in fitting the Dirichlet model.

These results show that the high private label purchase frequency is a feature which runs across most segments of the buying population. It is therefore not the result of just AB or single household buyers, or indeed any segment of buyers who are particularly loyal private label buyers. There are no signs of any buyer segmentation towards private labels over and above what is expected from theory given their market shares.

It is therefore unlikely that market segmentation causes the private label discrepancy. The assumption of a non-segmented market is largely fulfilled in practice.

5.6 SUMMARY AND CONCLUSIONS

In chapter 4 we found the main difference between brands and private labels was that private labels had a higher purchase frequency than both brands and than was predicted by the Dirichlet model. There were other differences relating to repeat, sole and duplicate buying rates, but these are dealt with in chapters 6 and 7.

The objective of this chapter was to determine why private labels had a higher purchase frequency. Was it because they attracted a higher level of repeat buying loyalty or is there some other explanation?

A variety of explanations were examined, and we have shown that once their limited availability and consequently mis-specified population at risk is accounted for, the discrepancy is largely overcome. This suggests that private labels do not attract a higher level of repeat-buying loyalty in respect of their penetration and purchase frequencies.

This result has been explored in many ways; estimates of penetration were made so as to account for the population at risk differences, and analyses undertaken whereby brands and private labels have more equal populations at risk. The result is supported on the whole by each method used. Furthermore, other explanations have also been examined and these fail to account for the private label discrepancy.

It is important to account for discrepancies when interpreting buyer behaviour data. For example, if it was thought that private labels had higher repeat-buying loyalty than brands, this would have strategic implications for retailers and manufacturers. Any future analyses of a similar nature on private labels will therefore need to take into account the relevant population at risk before drawing conclusions from the data.

The main conclusion from this chapter is that private labels do not attract more repeat-buying loyalty than brands in respect of their penetration and purchase frequencies. Once a more relevant population at risk is used, they are bought much like any other brand or private label of a comparable size.

In summary, we find:

- * Private label purchase frequency seems higher than predicted because the observed penetration is under-estimated. Once this has been taken into account we find private label buying patterns are similar to those for brands and as predicted from theory.
- * It is not, as seemed initially, that the purchase rate is high. Rather that penetration is held down because the number of buyers is calculated from an over-estimated population of potential buyers in comparison to the average brand. When a more appropriate population at risk is estimated, penetration rises in such a manner as to largely account for the private label purchase rate.

- * Private label availability is much lower than for the average brand. Indeed in London the average brand has eight times the distribution of the average private label. Furthermore, as people switch between stores for their product field purchases, the opportunity to buy a given brand remains, whereas the opportunity to buy a specific private label does not. Therefore, it is not just limited availability from which private labels suffer, but the opportunity to buy them is also reduced as a consequence.
- * Of the three population at risk estimates, the evidence suggests that the true figure lies somewhere between the three. They all show that private labels have a smaller population at risk than the 650 continuous reporters used in chapter 4 analyses.
- * A mis-specified population at risk causes problems in calculating penetration. This has repercussions on all further buyer behaviour measures because they are all derived from the central relationship between penetration and purchase frequency. This has not been shown in this chapter, but in interpreting the results in chapter 4, such repercussions have been discussed in the text.
- * When private labels are aggregated so as to overcome their limited availability, their purchase rate falls in line with the rest of the market; similarly when purchasing within the store is examined, purchase rates are much in line with predictions; OBPL and Corona lend further support to the population at risk explanation because their buying patterns reflect their availability rather than whether the item is a brand or private label per se.
- * Private labels were found to be more expensive than minor brands, but cheaper than the brand leaders. They are available in much the same range of pack sizes as are brands. They satisfy the model assumptions of stationarity and an unsegmented market as do brands. They are bought by the same type of buyer as brands as far as demographic and socio-economic characteristics are concerned.
- * These findings have been shown to generalise. They do not just relate to Fruit Squash (London), though this was the only data set shown in detail. That private labels are on the whole bought much like brands has been

found to occur in UK and US data, for a variety of product fields, for different length time periods, for foods and non-foods and for seasonal and non-seasonal product fields.

- * That private labels have a distribution disadvantage was shown to be so for both product fields in both regions. However, the population at risk analyses were only undertaken for the London regions. This was because in Lancashire private label sample sizes are too small and data for the more liberal estimate of the population at risk was not made available.
- * Other researchers have noted the importance of accounting for differences in availability in studies of purchase behaviour though none have tested the case extensively in relation to private labels.

The evidence in chapter 5 shows that once private label limited availability is taken into account, the high average purchase frequency largely falls into line with the theory. Private labels are bought largely by the same kind of people in the same way as are brands, once market share differences have been taken into account.

In chapter 4, another difference related to the rate of sole buying by private label buyers which was somewhat higher than predicted. Once their limited availability is taken into account though, some of the difference still remains. This means it is in addition to the limited availability problem. This is analysed further in chapters 6 and 7.

We now know how people buy private labels, and that on the whole existing Dirichlet and NBD models can be used to describe private label purchase behaviour. However, there are some other deviations and we explore these in the next two chapters. The fact that private label purchase behaviour does largely follow the same patterns as brands enables us to examine them in more detail.

In Chapter 6, which follows, we examine private label purchase behaviour within store chains so that population at risk problems are overcome. This enables us to examine further the other differences which were identified between brands and private labels as well as comparing private label buying patterns for each store chain.

CHAPTER 6 : HOW PEOPLE BUY PRIVATE LABELS WITHIN STORE CHAINS

6.1 Introduction**6.2 Data Used In The Empirical Analyses****6.3 Purchase Behaviour Within Store Chains****6.3a Penetration And Average Purchase Frequency Within Store Chains**

Summary

6.3b Period To Period Buying Within Store Chains

Repeat Buying
New and Lapsed Buying
Summary

6.3c Item Purchase Frequency Distribution Within Store Chains

Summary

6.3d Product Field Buying Within Store Chains

Total Product Purchase
Share Of Local Requirements
Incidence and Rate Of Sole Buying
Summary Of Sole Buying Results
Incidence and Rate Of Duplicate Buying
Summary

6.4 Summary And Conclusions

6.1 INTRODUCTION

So far we have concentrated on how people buy brands and private labels in the product field. In this chapter, we move away from a purely product field focus to concentrate on how people buy items within individual store chains.

This is important for three reasons.

In chapters 4 and 5, we found that the values of the components of the sales equation differed for brands and private labels. However, once differences in the populations at risk were allowed for, they were bought in much the same way, and largely in line with the theory. The main exception to this was the rate of buying by sole buyers which is so high that it is not compensated for by the population at risk adjustment. However, in order to determine which differences are population at risk effects, and which, if any, are additional results, analyses need to be undertaken after having allowed for the different populations at risk. This is achieved by examining purchasing at the within store level.

Secondly, past research has mainly been without reference to the store of purchase. The store interface is particularly important in any discussion of private labels because they are store specific, and retailers use them to help develop a distinct store image. Private labels are said to differentiate one retailers stock from another (Frank and Boyd 1965, Simmons and Meredith 1984), thus leading to a competitive advantage for the retailer concerned. However, for such a strategy to be effective, one retailers private label must be seen to be different to anothers, and this should be reflected in the purchase behaviour of their customers. Indeed, it may be that some stores' private labels are bought differently to those of other stores; or that purchasing in stores with private labels differs from in those without. Within store analyses enable us to examine how people buy specific stores' private labels, and whether they do so in the way retailers strategic use of them implies.

Thirdly, there have been few studies on purchasing within store chains. Research in both the UK and USA has shown that the purchase of fast moving consumer goods at a particular store group is highly predictable using what have hitherto been called brand choice models (Kau and Ehrenberg 1984, Uncles and Ehrenberg 1988, Lamb 1989, Lamb and Goodhardt 1988, Ellis and Uncles 1989). However there has been no behaviourist study focussing specifically on private labels and store choice. Some early work on store choice using the NBD model did include private labels as part of the analysis (Kau 1981). Kau found that buyers at stores with strong private

label ranges were less likely to buy other stores' private labels, but that this did not prevent them from buying brands at other stores. Another store choice study, which included private labels in the aggregate, found they were bought much in line with the theory (Lamb 1989).

Therefore, the objectives of this chapter are threefold; to identify any other differences between brand and private label purchase behaviour which exist once population at risk adjustments have been made; to determine how specific private labels are bought, and whether purchase behaviour differs by store chain; and finally to examine private label purchasing at the within store level. We ask such questions as: are there any differences in consumer buying patterns in those stores which offer private labels as compared to those without? Do people buy the Sainsbury private label differently to the Tesco private label? Indeed does the presence of a private label in the store appear to influence consumer purchasing from what we expect from theory?

This chapter consists of three parts. In section 6.2 we outline the data analysed in the empirical section. Then in section 6.3 we adopt the same analysis procedure as in chapter 4; the components of the sales equation are examined; then buying from one time period to another; next the purchase frequency distribution for different items within each store chain; and then buying across the entire product field. Finally, in section 6.4, results are summarised and some early conclusions are drawn.

6.2 DATA USED IN THE EMPIRICAL ANALYSES

48 week panel data for Fruit Squash and Liquid Fabric Conditioner in London and Lancashire are used. Unfortunately store data were not made available for the other three product fields examined in chapter 4. Nevertheless, the results can still be generalised over different conditions because the two product fields and regions are quite different in their composition of retail stores and private label market shares. Furthermore, we can draw on the results from earlier studies to a limited degree.

London and Lancashire have different retail mixes; London is dominated by Sainsbury and Tesco with 37% and 15% of the Fruit Squash market respectively and they also have extensive ranges of private labels. By contrast, in Lancashire, Asda and KwikSave are market leaders with 19% and 18% shares of the Fruit Squash market and only Asda offers private labels (AGB 1988). Private labels have 56% of the Fruit Squash market in London and 20% in Lancashire, thus providing an

interesting contrast. Liquid Fabric Conditioner sales are similarly diverse.

Throughout the within store analyses, detailed results are shown for Fruit Squash purchasing in four store chains; KwikSave and Sainsbury in Lancashire, and Tesco and Sainsbury in London. These have been chosen because they cover a range of private label policies. They represent stores with Fruit Squash market shares from 5% to 37%, and within-store private label shares in Fruit Squash from zero to 72% (Table 6.1). Results for Fabric Conditioner, other stores and regions are presented in summary form at the end of each section.

Table 6.1 : Data Used For Within Store Analyses

Region	Store	Share Of Product Field In Store		Private Label Share In Store	
		FS	FC	FS	FC
Lancashire	KwikSave	18	23	0	0
	Sainsbury	5	4	51	52
London	Tesco	15	14	53	22
	Sainsbury	37	37	72	41
Average		19	20	44	29

Note : FS Fruit Squash, FC Fabric Conditioner

Much of the comparison is between buying patterns in stores with and without private labels, as well as between stores with differing private label shares. However, it should be noted that in this study KwikSave is the only itemised store without private labels. This means our interpretation of buying in stores without private labels is dependent on how items are bought in KwikSave. If KwikSave is representative of stores without private labels, then our comparison is reliable. If buying patterns in KwikSave are for some reason different, then the comparison between stores with and without private labels is not valid. However, we believe that KwikSave is indicative of what would be found at similar stores because buying patterns are closely predicted by the two general stochastic models, and stores with few private labels are bought similarly to those with many.

Furthermore, analyses on Asda Fabric Conditioner, where no private labels were

offered at the time of the study show that purchasing patterns are much in line with theory. This is not completely comparable because Asda has private labels in other product fields, but it still supports the KwikSave results. Nevertheless, this limitation should be taken into consideration when interpreting the results.

Within store analyses suffer from problems of small sample sizes because analyses are restricted to within one store chain. When results are particularly deviant for this reason they are omitted from the average, and this is noted as and when it occurs.

Analyses follow the same structure as adopted in chapter 4, starting with aggregate measures, then breaking them down into more detail. Penetration and average purchase frequency are examined first; then we look at how people buy items from one time period to the next; thirdly the distribution of purchases is examined; and finally we look at how people spread their purchases in individual store chains across the product field.

6.3 PURCHASE BEHAVIOUR WITHIN STORE CHAINS

In chapter 4 we showed that the success of an item in the market place depends principally on the number of people buying it, and to some extent the frequency with which they buy the brand. Similarly the performance of an item within a particular store depends most importantly on the number of store shoppers buying it and their average number of purchases. These two components of the sales equation are examined below.

6.3a Penetration And Average Purchase Frequency Within Store Chains

When analyses are confined to within store chains, the high private label purchase rate is no longer consistently evident as we detail below. This means that once the population at risk is correctly specified, the number of people buying, and the rate at which they buy is similar for all items, and much in line with the theory. So we can now examine private labels in more detail.

We might expect that fewer people than predicted visit KwikSave for their Fruit Squash purchases than visit Sainsbury because the former has no private label alternative. However, the model fit (Table 6.2) for the overall average is close despite the fact that KwikSave is a purely branded operation and Sainsbury (London) has over 72% of its Fruit Squash sales in private label (Table 6.1). The observed and theoretical average penetration across both stores in each region are equal (after rounding). Purchase frequency is also

closely predicted on average. In Lancashire, the average buyer makes 4.1 (3.9) purchases, whereas in London the average buyer makes 3.7 (4.0) purchases.

The Double Jeopardy pattern is largely followed in stores with and without private labels. There are some discrepancies, but these are not systematic; for example, Robinsons in Sainsbury (Lancashire) and OB in Sainsbury (London). However, the former is a small brand and the latter an amalgamation of brands.

These results suggest that the presence of a private label in a store is not reflected by a difference in the way in which brands are bought over and above some substitution effects as the private label is included in the buyers repertoire. The fact that many people include the private label in their repertoire is an important result which is developed more in chapter 9.

Table 6.2 : Penetration And Average Purchase Frequency Within Store Chains For Fruit Squash (48 Weeks)

Item	O	b T	w O	T	Item	O	b T	w O	T
LANCASHIRE					LONDON				
KwikSave					Tesco				
Robinsons	15	(15)	6.0	(6.1)	Tesco pl	11	(12)	5.4	(5.2)
Vimto	10	(11)	5.9	(5.4)	Quosh	7	(6)	3.4	(3.9)
GeeBee	6	(5)	4.2	(4.5)	Robinsons	7	(5)	2.8	(3.7)
Sunland	6	(5)	3.7	(4.4)	RB	2	(1)	2.8	(3.3)
Kia-Ora	3	(2)	2.3	(4.1)	OB	2	(1)	2.1	(3.3)
Average	9	(9)	5.0	(5.1)		6	(5)	3.3	(3.9)
Sainsbury					Sainsbury				
Sainsbury pl	7	(7)	3.8	(3.8)	Sainsbury pl	30	(29)	6.6	(6.8)
Robinsons	2	(4)	4.7	(2.7)	Robinsons	10	(10)	4.0	(4.0)
Vimto	2	(2)	2.4	(2.3)	OB	5	(3)	2.3	(2.6)
OB	2	(1)	1.3	(2.1)	RB	4	(3)	3.4	(3.6)
					Kia-Ora	3	(3)	3.5	(3.6)
Average	3	(4)	3.1	(2.7)		10	(10)	4.0	(4.1)
Overall Average	7	(7)	4.1	(3.9)		8	(8)	3.7	(4.0)

Note : average 24 week base used in fitting the Dirichlet model

There are no differences, in respect of penetration and purchase frequency, between Sainsbury and Tesco private labels once their relative market shares have been taken into account. Within the store, they follow the same patterns of buyer behaviour as are predicted from theory. For example, the model fit is close for the Sainsbury (London) private label which is bought by 30% (29%) of people, 6.6 (6.8) times. Similarly, the Tesco private label is bought by 11% (12%) of people, 5.4 (5.2) times. More people buy the Sainsbury private label than Tesco's because it has a larger in-store market share, 72% as compared to 54% for the Tesco private label. Indeed, not only are the individual stores private labels bought in the same way, they are bought much like any comparable brand.

There are some deviations from the model which are mainly due to small sample sizes (Table 6.2). For example, in Sainsbury (Lancashire), the average purchase frequency of the three smaller brands differs from the theoretical values, and there are similar discrepancies in the other three stores. However, such deviations do not tell us anything about small items or private labels in particular because they are not consistent, in either their direction or size. Furthermore, they affect stores with and without private labels and so do not interfere with the main comparison.

These results generalise. They occur for the average brand and private label in 14 stores, 2 regions, two product fields and where private labels market shares vary from zero to 72% (Table 6.3). The fit of the model is close for the overall average; penetration is predicted exactly (after rounding), 5% for the average brand and 10% for the average private label; and the average purchase frequencies differ little, 3.0 (3.0) and 4.1 (4.0) for the average brand and private label respectively. There are no consistent deviations associated with the presence of private labels, and this is so for each store's private label.

Table 6.3 : Penetration And Average Purchase Frequency For The Average Brand And Private Label Within Store Chains (48 weeks)

		Average Brand				Average Pl			
		b		w		b		w	
		O	T	O	T	O	T	O	T
Fruit Squash									
London	Sainsbury	6	(5)	3.3	(3.5)	30	(29)	6.6	(6.8)
	Tesco	5	(4)	2.7	(3.6)	11	(12)	5.4	(5.2)
	Coop	2	(2)	2.3	(2.4)	8	(9)	5.2	(4.7)
Lancashire	KwikSave	9	(9)	5.0	(5.1)	*	*	*	*
	Coop	4	(7)	4.1	(2.6)	17	(16)	3.3	(3.5)
	Sainsbury	2	(2)	2.8	(2.4)	7	(7)	3.8	(3.8)
	Tesco	2	(3)	4.4	(3.0)	7	(7)	4.2	(3.9)
Average		4	(4)	3.5	(3.2)	13	(13)	4.8	(4.7)
Fabric Conditioner									
London	Sainsbury	7	(7)	2.5	(2.8)	16	(16)	3.9	(4.0)
	Tesco	5	(5)	2.5	(2.7)	6	(5)	2.2	(2.7)
	Coop	3	(3)	2.4	(2.7)	3	(3)	2.7	(2.9)
Lancashire	KwikSave	9	(10)	3.4	(3.5)	*	*	*	*
	Coop	6	(5)	2.4	(2.6)	6	(7)	2.8	(2.7)
	Sainsbury	2	(2)	1.4	(1.4)	4	(6)	3.5	(2.6)
	Tesco	4	(3)	3.5	(3.8)	4	(5)	4.7	(4.0)
Average		5	(5)	2.6	(2.8)	7	(7)	3.3	(3.2)
Overall Average		5	(5)	3.0	(3.0)	10	(10)	4.1	(4.0)

Note : average 24 week data used in fitting the Dirichlet model; * means no private labels in that store.

The main difference between a store which offers a private label from one that does not, such as KwikSave, is that the private label tends to be the within-store brand leader (Table 6.4). This occurs on 12 (of 16) occasions; the Sainsbury private label is brand leader on all four occasions, Tesco three times and the Coop twice.

Private labels are more often the within-store brand leader in Fruit Squash than Fabric Conditioner. Indeed, only the Sainsbury private label is brand leader in both product fields. This raises many questions; why private labels achieve such high market shares; why these vary among different store's private labels; why each store's private label share is not uniform by product field and region; and why shares vary by product field. Some of these questions are addressed in the discussion in chapter 9.

The lowest within-store share for a private label is 21% (KwikSave excluding) for Fruit Squash in Morrisons (Lancashire). There are therefore no "small" private labels in the stores examined. This suggests that when a private label is offered it obtains a sizeable market share, or that when it does not, it is de-listed.

The Sainsbury private label is particularly successful. Neither the brand leader in KwikSave, nor those in other stores, achieve the market share level of the Sainsbury private label. This has on average a 60% within-store share across both product fields. Even in Fabric Conditioner, where private label shares are lower, the Sainsbury private label still has a relatively high share of 58% on average. It is also interesting to note that its share of private label varies by region from 41% to 71%. These ideas are developed more in chapter 9.

Table 6.4 Private Label Market Shares And Positions In Store Chains (48 weeks)

		% pl in store	Position in store	Number of brands in store	% market share of largest brand
Fruit Squash					
London	Sainsbury	72	1	5	15
	Tesco	54	1	6	20
	Coop	64	1	4	16
	Waitrose	64	1	4	19
	Safeway	44	1	2	18
Lancashire	Sainsbury	51	1	6	19
	Tesco	54	1	5	20
	Coop	36	1	6	23
	Morrison	21	3	5	28
	Asda	26	1	5	17
	KwikSave	[0]		4	44
Average		49		5	22
Fabric Conditioner					
London	Sainsbury	41	1	3	33
	Tesco	23	3	2	44
	Coop	23	3	3	35
Lancashire	Sainsbury	75	1	1	17
	Tesco	46	1	2	29
	Coop	29	2	3	38
	KwikSave	[0]		3	55
Average		40		3	36
Overall Average		45		4	29

Note : [] means the figure is excluded from the average.

Summary

Penetration and purchase frequency within the store are similar for brands and private labels. Therefore, results in this section support the population at risk

explanation further. Once it is correctly specified, private labels are bought in much the same way as brands, and both are similarly predicted by the Dirichlet model. Furthermore, the same patterns of buyer behaviour that have already been identified for brands and now private labels (chapter 4), can also be generalised to the within-store level. This means we can compare private labels with brands using the model predictions as our norm. However, only two product fields have been examined and this limitation needs to be borne in mind in interpreting the results.

Buying patterns in stores with private labels are similar to those in KwikSave, and both are closely predicted by the model. The presence of a private label within the store does not for example attract more frequent buyers to the product field. There are some market share substitution effects as most people include the private label in their repertoire, but once these are taken into account, the private label is bought much like any other large brand in the store.

Though some private labels achieve higher within-store market shares than others, once these differences are taken into account, people buy one private label in much the same way as any other. For example, Sainsbury private label buyers do not comprise a more select group of heavy buyers than Coop private label buyers. Buyers of both private labels are on the whole as predicted by the model.

When private labels are available, there is a tendency for them to be the within-store brand leader. Why they achieve this level of success and why this varies by private label, product field and region are interesting questions which are discussed in chapter 9. However, given they are in this position, they are bought just like any other brand leader. Indeed, people buy the private label as they do the brand leader in KwikSave, so there is nothing special in the way the private label is bought, but more in the market share level it achieves.

Some private labels are within-store brand leaders more often than others. For example, the Sainsbury private label is brand leader more often than any other private label in the two product fields examined. It also achieves a considerably higher market share than any other private label or brand. This is examined in more detail in the following sections, and we discuss reasons for

it in chapter 9.

We also find that the share of private labels in each product field results from the contribution of many stores' private labels. For example, in Fruit Squash (London), the share of private labels within the store ranges from 44% to 72%. So the total private label share in the product field is not just a result of one or two larger stores having say 90% private label shares, but many stores with more similar shares. Indeed, there are no "small" private labels in the two product fields examined. The lowest within-store market share was 21% for Fruit Squash in Morrisons (Lancashire). This means that either all private labels achieve a sizeable market share, or that if they do not, they are de-listed.

Having now shown that the aggregate measures of buyer behaviour for brand and private label purchasing within the store are much in line with the theory, we can examine more detailed measures using the model predictions as our norm. There are some interesting differences between the market shares achieved by each stores' private label and more detailed analyses enable us to elaborate further. The fact that within-store analyses overcome the population at risk discrepancy means that we can look at sole buying for example, which was particularly high for private labels in chapter 4. It may be that private labels attract more sole buying loyalty than the average brand, or that some private labels attract more loyalty than others. Such differences would not show through in the aggregate measures of buyer behaviour.

First, we examine how people buy items within the store from one time period to the next; the aim being to identify any differences in the repeat purchasing behaviour of brands and private labels, and any differences in these patterns by store. Repeat buying was not addressed in detail in Chapter 4 analyses, so more details are provided below. We return to using 24 week data because we need two equal length time periods for repeat buying analyses and have 48 week data.

6.3b Period To Period Buying Within Store Chains

Patterns of period to period repeat buying were not examined in detail in chapter 4. This was primarily because the focus was largely on the high private label purchase rate, and secondly because the model was found to deviate unsystematically. The latter reason made it difficult to interpret results

in any meaningful manner. Repeat buying is examined in more detail in the within-store analyses because at least now we know that the population at risk is more correctly specified, and that private labels are on the whole bought much in line with the theory.

Even within the store, there is still a discrepancy which needs to be pointed out before interpreting the results. The incidence of repeat buying tends to be below the predicted level. This was also found to occur in analyses of product field purchasing, and purchasing across two product fields (chapter 7).

In Table 6.5, there are four occasions where this is not so; the three smaller brands in Sainsbury (Lancashire) and Kia-Ora in KwikSave. In Sainsbury (Lancashire), Robinsons incidence of repeat buying is higher than predicted, 83% (72%), because it has a high purchase frequency (Table 6.2). The other three anomalies probably arise because they are small sample bases of only 13 to 35 buyers. Results from such samples are often deviant because they are greatly influenced by the behaviour of a few individuals. They do not say anything about small brands though because deviations are unsystematic. Indeed other small brands have incidences of repeat buying below the predicted level; for example, Robinsons Barley (RB) and Other Brands (OB) in Tesco have 25% (59%) and 20% (50%) respectively.

The fact there is a fairly consistent over-prediction does not tell us anything about private labels because it affects all items similarly. It is a general problem with the model when applied to repeat buying. However, this deviation does not prevent us from using the model as a basis for comparison because we can take it into account before making comparisons. We show below that repeat buying patterns are similar for brands and private labels, and there are no additional differences in this respect once the population at risk adjustment has been made.

Furthermore, the incidence of repeat buying is similar in stores with and without private labels (Table 6.5). For example, in KwikSave the average incidence is 56% (72%) and this is similar to Tesco stores, 50% (66%). (Though it seems that repeat buying for Sainsbury (Lancashire) is high, this is distorted by small brands as explained above). So the presence of a private label in the store does not mean for example, that buyers are more likely to repeat buy items in the store than they are in KwikSave. Buying patterns in both stores

are similarly predicted by the model.

On average the rate of buying by repeat buyers is well predicted in stores with and without private labels. In Lancashire they make an average of 4.0 (4.1) purchases, and in London, 4.0 (3.7). Though two of the three private labels have a higher rate of repeat buying than predicted, Tesco 5.5 (4.8) and Sainsbury (Lancashire) 5.2 (3.4) times, this does not generalise and also occurs for some of the brands.

Table 6.5 : Incidence And Rate Of Repeat Buying Within Store Chains For Fruit Squash (24 weeks)

LANCASHIRE					LONDON				
Item	br		wr		Item	br		wr	
	O	T	O	T		O	T	O	T
KwikSave					Tesco				
Robinsons	54	(75)	5.3	(5.4)	Tesco pl	54	(73)	5.5	(4.8)
Vimto	72	(74)	4.5	(5.3)	Quosh	50	(65)	3.9	(3.2)
GeeBee	59	(68)	3.3	(3.7)	Robinsons	46	(61)	3.3	(2.8)
Sunland	36	(69)	4.3	(3.9)	[RB	25	(59)	2.0	(2.7)]
[Kia Ora	88	(49)	2.7	(2.0)]	[OB	20	(50)	10.0	(2.1)]
Average	56	(72)	4.4	(4.6)	Average	50	(66)	4.2	(3.6)
Sainsbury					Sainsbury				
Sainsbury pl	61	(66)	5.2	(3.4)	Sainsbury pl	68	(76)	5.2	(5.2)
Robinsons	83	(72)	3.4	(4.7)	Robinsons	51	(68)	4.7	(3.7)
Vimto	71	(54)	1.8	(2.3)	OB	33	(56)	1.9	(2.4)
[OB	33	(12)	1.7	(1.1)]	RB	46	(66)	3.5	(3.4)
Average	72	(68)	3.5	(3.5)	Average	50	(67)	3.8	(3.7)
Overall Average	64	(68)	4.0	(4.1)	Overall Average	46	(67)	4.0	(3.7)

Note : average 24 week base used in fitting the NBD model; [] not included in the average.

Each store's private label is bought from one time period to the next in much the same way. There is no consistent evidence to suggest that the Sainsbury private label, for example, attracts more repeat buying loyalty than any other.

These results generalise. The low incidence of repeat buying occurs more widely for both brands and private labels (Table 6.6). (Figures in this table include all items in the product field, unlike Table 6.5.) The overall average incidence of repeat buying by brand buyers was 47% (55%) and for private labels 56% (67%). Rates of repeat buying by brand and private label buyers are both slightly higher than predicted by the model; on average 3.2 (2.8) and 4.2 (3.7) respectively.

Table 6.6 : Incidence And Rate Of Repeat Buying For The Average Brand And Private Label Within Store Chains (24 weeks)

		Brands				Private Labels			
		br		wr		br		wr	
		O	T	O	T	O	T	O	T
Fruit Squash									
London	Sainsbury	38	(65)	5.2	(3.4)	68	(76)	5.2	(5.2)
	Tesco	35	(59)	4.8	(2.7)	54	(73)	5.5	(4.8)
	Coop	52	(44)	2.5	(2.3)	69	(72)	5.2	(4.5)
Lancashire	KwikSave	62	(67)	4.0	(4.1)	*	*	*	*
	Sainsbury	62	(46)	2.3	(2.7)	61	(66)	5.2	(3.4)
	Tesco	54	(58)	3.1	(2.6)	52	(73)	4.7	(4.9)
	Coop	52	(62)	3.0	(3.8)	55	(63)	5.0	(2.9)
Average		51	(57)	3.6	(3.1)	60	(71)	5.1	(4.3)
Fabric Conditioner									
London	Sainsbury	46	(55)	3.3	(2.4)	67	(67)	3.2	(3.3)
	Tesco	40	(62)	3.0	(2.9)	46	(54)	2.4	(2.2)
	Coop	37	(52)	3.2	(2.4)	47	(58)	2.3	(2.5)
Lancashire	KwikSave	49	(64)	3.5	(3.2)	*	*	*	*
	Sainsbury	28	(18)	1.0	(1.2)	55	(64)	2.8	(3.1)
	Tesco	54	(64)	3.1	(3.1)	52	(70)	4.7	(4.2)
	Coop	41	(54)	2.1	(2.3)	43	(62)	4.4	(2.8)
Average		42	(53)	2.7	(2.5)	52	(63)	3.3	(3.0)
Overall Average		47	(55)	3.2	(2.8)	56	(67)	4.2	(3.7)

Note : average 24 week base used in fitting the NBD model; * means no private labels available in that store

People repeat buy in stores with private labels in the same way as they do in KwikSave. There are no systematic discrepancies in either the incidence or rate in accordance with the presence of private labels. Therefore, offering a private label does not mean that more people will continue to buy items in the store more often than at a store without private labels. Despite offering something unique to the store, repeat buying patterns are no different in this respect.

Furthermore, each store's private label is bought in much the same way as any other. The Sainsbury private label in Fabric Conditioner (London) has an incidence of repeat buying which is as predicted by the model. This is unusual because other private labels are lower than predicted. However, this does not generalise to other Sainsbury private labels, nor to other private labels in general. It is peculiar to that data set.

Not everyone is a repeat buyer from one period to the next. There are also those who are new buyers to the analysis period and those who only bought in the first of two periods. These related measures of period to period buying are the complement to repeat buying and so results are briefly summarised below.

New And Lapsed Buying

There is no difference between the incidence and rate of new and lapsed buying between stores with and without private labels, nor between the private labels of individual store chains. The fit of the model is close on average for the rate of buying by new buyers, but the incidence is consistently higher than predicted, being the opposite to that found in repeat buying.

Summary

The incidence and rate of repeat buying within the store are similar for brands and private labels. NBD predictions take account of any differences in the components of the sales equation so the population at risk adjustment does not improve the fit of the model as happens with the Dirichlet. The fact that brands and private labels are similarly predicted by the NBD model means that there are no differentiating measures over and above their market share differences.

Period to period repeat buying within individual store chains for both brands and private labels is similar to item choice in the market place more generally.

Both exhibit similar patterns of purchase behaviour and as such are predictable by the same stochastic models.

There is no sizeable difference in period to period repeat buying behaviour within a store offering a private label and one that does not. The fact that the store offers a private label does not mean for example, that its products attract a higher level of repeat buying than occurs in a store with no private labels. Nor does it affect the way people buy other brands in the product field, over and above some substitution with the private label as it becomes part of the buyers repertoire. The private label is bought just like any other brand leader in this respect, despite being unique to a particular store chain.

Individual store's private labels are mostly bought in line with their market shares, once the consistent over-prediction for the incidence of repeat buying is taken into account. So the Sainsbury private label, for example, does not always seem to result in people buying at that store chain more so than any other brand in the store, nor more so than any other store's private label.

The incidence of repeat buying within the store consistently deviates from the model predictions, and this makes it more difficult to interpret results. Though this deviation is consistent and interesting, it does not affect the main comparison between brands and private labels as it affects both similarly. Therefore, no serious attempt is made to solve this technical problem because it is outside the scope of the thesis.

So far we have examined the numbers buying and their rates as an average across the population. Yet within the average, people differ in their rates of purchase. Therefore, we now examine the distribution of purchase frequencies across the population for within-store buying. This is to determine whether there are any differences in the purchase frequency distributions for brands and private labels, and for buying generally in stores with and without private labels.

6.3c Item Purchase Frequency Distribution Within Store Chains

This distribution shows how often buyers purchase in a given time period. The shape of the distribution is generally a downward sloping positively skewed curve which can be closely predicted by the NBD model. With any fast moving consumer good, there is a tendency for few people to be heavy buyers of an

item, and the majority to be light buyers.

We show below that both brands and private labels have similar positively skewed distributions (Table 6.7). This means that once their market shares have been allowed for, there are no further differences between them in this respect. We can therefore examine the results which follow using the NBD as the norm.

However, one consistent difference between the observed and theoretical figures is that the distribution is more skewed towards light buyers. This was also found for analyses in chapter 4 (Table 4.12 page 106) and we discuss reasons for it in chapter 9. There are approximately 20% more light buyers than is predicted by the model. For example, in Lancashire 51% (42%) of buyers are light buyers. The excess in light buyers comes predominantly from medium buyers 32% (39%), and less so from heavy buyers 17% (19%). In London, the excess comes completely from medium buyers on average.

There are only four exceptions to this at the individual level which include both brands and private labels in two of the four stores; GeeBee and Kia-Ora in KwikSave; the Sainsbury (London) private label and Robinsons Barley in Sainsbury (London). The fit of the model is much closer for these.

Table 6.7 : Item Purchase Frequency Distribution Within Store Chains For Fruit Squash (48 weeks)

Item	1		2-5		6+			1		2-5		6+	
	O	T	O	T	O	T		O	T	O	T	O	T
LANCASHIRE							LONDON						
KwikSave							Tesco						
Rob	36	(31)	37	(37)	27	(32)	Tesco pl	40	(32)	33	(38)	27	(30)
Vimto	43	(32)	32	(35)	25	(34)	Quosh	49	(41)	30	(41)	21	(18)
GeeBee	35	(37)	39	(41)	26	(22)	Rob	53	(46)	30	(43)	17	(11)
Sunland	53	(39)	34	(41)	13	(20)	RB	60	(46)	30	(42)	10	(12)
Kia-Ora	52	(52)	44	(40)	4	(8)	OB	67	(55)	26	(39)	7	(6)
Average	44	(38)	37	(39)	19	(23)		54	(44)	30	(41)	16	(15)
Sainsbury							Sainsbury						
Sains pl	52	(39)	29	(42)	19	(19)	Sains pl	28	(28)	37	(38)	34	(34)
Robinsons	42	(36)	33	(39)	25	(25)	Robinsons	54	(38)	24	(41)	22	(21)
Vimto	62	(51)	30	(40)	8	(9)	OB	55	(51)	39	(41)	6	(8)
OB	71	(67)	21	(30)	7	(2)	RB	39	(42)	39	(41)	22	(17)
							Kia-Ora	64	(41)	28	(41)	8	(18)
Average	57	(48)	28	(38)	15	(14)		47	(40)	35	(40)	18	(20)
Overall Average	51	(42)	32	(39)	17	(19)		51	(42)	31	(41)	18	(17)

Note : average 24 week data used in fitting the NBD model.

We might expect stores with private labels to have more heavy buyers than those without because it is often said that private labels attract more loyalty from their buyers than their branded counterparts (Simmons and Meredith 1984, Cunningham 1961, Retail Business 1971). However, we find that the same purchase frequency distribution exists on average for stores with and without them (Table 6.7). For example, on average in the two Lancashire stores, 51% (42%) bought any item once; 32% (39%) bought between 2 and 5 times; and 17% (19%) bought over 6 times. A similar pattern occurs for the two London stores.

Furthermore, there are no consistent differences between the purchase frequency distribution of each store's private label.

These results generalise across all 14 stores. We find that brands and private labels have similar frequency distributions. These are slightly more skewed towards light buyers than is predicted from theory. However, the difference is smaller when generalised across 24 stores because the Fruit Squash distribution is more positively skewed than Fabric Conditioner due to its seasonal nature. This is discussed more in chapter 8. The overall brand average shows that 55% (50%) bought once, 33% (38%) bought between two and five times and 13% (12%) bought over 6 times. The distribution for the overall average private label is similar; 40% (36%) bought once, 37% (40%) bought between 2 and 5 times and 23% (24%) bought over 6 times.

There are some slight discrepancies. Four private labels and one brand does not have an excess of light buyers; these include 3 Sainsbury private labels and the Coop (London) Fruit Squash private label. This suggests that the Sainsbury private label in particular has more heavy and medium buyers than the average item. The Coop result does not generalise any further.

Table 6.8 : Item Purchase Frequency Distribution For The Average Brand And Private Label Within Store Chains (48 weeks).

Item	Brands						Private Labels					
	1		2-5		6+		1		2-5		6+	
	O	T	O	T	O	T	O	T	O	T	O	T
Fruit Squash												
London	Sainsbury	53 (43)	33 (42)	15 (16)			28 (28)	38 (38)	34 (34)			
	Tesco	57 (47)	29 (41)	14 (12)			40 (32)	33 (38)	27 (30)			
	Coop	63 (58)	28 (34)	9 (8)			39 (34)	36 (37)	25 (28)			
Lancs	KwikSave	44 (38)	37 (39)	19 (21)			* *	* *	* *			
	Sainsbury	58 (51)	29 (37)	13 (12)			52 (39)	29 (42)	19 (19)			
	Tesco	60 (54)	31 (39)	9 (7)			40 (33)	33 (38)	27 (29)			
	Coop	63 (58)	28 (34)	9 (8)			39 (34)	37 (28)	24 (28)			
Average		57 (50)	31 (38)	13 (12)			40 (33)	34 (37)	26 (28)			
Fabric Conditioner												
London	Sainsbury	58 (53)	32 (38)	10 (19)			36 (37)	46 (43)	18 (20)			
	Tesco	61 (50)	26 (39)	13 (11)			55 (51)	40 (37)	5 (11)			
	Coop	31 (26)	37 (47)	32 (27)			13 (18)	56 (46)	31 (36)			
Lancs	KwikSave	57 (44)	28 (41)	15 (15)			* *	* *	* *			
	Sainsbury	67 (75)	33 (24)	0 (1)			37 (41)	44 (42)	19 (17)			
	Tesco	42 (41)	48 (45)	10 (14)			41 (35)	30 (42)	29 (23)			
	Coop	56 (51)	35 (41)	9 (8)			55 (45)	33 (43)	12 (12)			
Average		53 (49)	34 (39)	13 (13)			40 (38)	42 (42)	19 (20)			
Overall Average		55 (50)	33 (38)	13 (12)			40 (36)	37 (40)	23 (24)			

Note : average 24 week data used in fitting the model; * means no private labels are available in that store.

Summary

The purchase frequency distributions for brands and private labels are similar.

Both have slightly more light buyers than predicted at the expense of medium and heavy buyers. There are no other consistent differences between brands and private labels in this respect once their market shares have been taken into consideration.

The excess of light buyers was also found to occur in chapter 4 analyses (Table 4.12). This means there are more light buyers in the five product fields examined than is predicted from theory. However the overall difference in both chapters only amounts to an excess of some 5% of light buyers. The fact it is consistent is of more note than the size of the deviation.

The purchase frequency distribution is similar for stores with and without private labels on average. The presence of a private label in the store does not mean that people buy any more or less frequently than they do in KwikSave, nor does it affect the way in which competing brands are bought within the same store chain.

Each store's private label (Sainsbury excluding) has a similar positively skewed purchase frequency distribution which is also similar to that for any comparable brand. A specific private label does not consistently attract more heavy buyers than any other, once market shares have been allowed for. However, three of the four Sainsbury private labels have more medium and heavy buyers than their brand and private label counterparts. This suggests that the Sainsbury private label tends to attract slightly more repeat buying loyalty. Such differences are discussed in chapter 9.

Finally, the purchase frequency distribution within individual store chains for all items are similar to those in the market place more generally (section 4.2c). This means that purchase behaviour at the within store level can also be described by the same two stochastic models.

So far we have examined purchasing of one item at a time within a store and found that on the whole private labels are bought much like any other brand. Their presence does not affect purchase behaviour in the store from what is expected from theory; nor are there any major differences between each store's private label.

However, most people buy a number of different items, even within the same product field. We now examine how people spread their purchases across the product field in order to identify whether there are any differences in the purchase behaviour between brands and private labels, and in stores with and without them. We pay particular attention to sole buying patterns which differed for private labels in chapter 4 (section 4.2d).

6.3d Product Field Buying Within Store Chains

Three main measures of buyer behaviour are examined; total product purchasing, sole and multi-item buying. Together, they provide a detailed picture of which items are bought and how often, how many buyers are 100% loyal, and how many switch between different items within the store.

This section is relevant to the question of whether private labels provide the retailer with more loyalty than a brand, and whether this differs by private label. If so, it would show up as higher loyalty to the private label than the average brand and than is predicted by the model. We have already shown in section 6.3a that private labels tend to be the within-store brand leader. This means they will attract more loyalty simply because they are larger than any other item in the store. However, they do not attract more loyalty than the brand leader in KwikSave, so it is mainly a market share effect, rather than anything specifically to do with the fact it is a private label.

Therefore, the real question we address is do private labels attract "even more" loyalty once market share differences have been accounted for? Only then would the retailer gain more loyalty than from offering another large brand. And even then, the private label should attract more loyalty in this respect than any other retailer's private label, otherwise there is no competitive advantage in this respect for the retailer concerned.

We return to using the Dirichlet model because the NBD only caters for one item at a time. 48 week data is used throughout this section.

Total Product Purchase

Here we examine buyers total rate of Fruit Squash purchasing in individual store chains. The well-established patterns of buying behaviour were discussed in more detail in section 4.2d (page 107), and so are not reviewed again here.

Product purchase rates for brands and private labels are closely predicted by the Dirichlet model (Table 6.9); on average buyers at the two stores in Lancashire and London make 10 (11) and 11 (11) Fruit Squash purchases in 48 weeks. This means that once market shares are allowed for, there are no additional differences in this respect.

There are no systematic differences in product purchase rates between those

stores with private labels and those without. However, the product purchase rates in the Sainsbury (Lancashire) store chain are on average lower than those in the other three stores. This is because the rate of purchasing overall is lower (Table 6.2). The close fit of the model means that buyers in all 4 stores have the same rate of product field purchasing as predicted from theory. Though discrepancies occur for small sample sizes, they do so in stores with and without private labels.

Table 6.9 : Product Purchase Rates Within Store Chains For Fruit Squash (48 weeks)

Item	wp		Item	wp	
	O	T		O	T
LANCASHIRE			LONDON		
KwikSave			Tesco		
Robinsons	11	(11)	Tesco pl	8	(8)
Vimto	11	(11)	Robinsons	9	(10)
Sunland	11	(14)	Quosh	9	(10)
GeeBee	10	(14)	OB	11	(11)
Kia Ora	16	(15)	RB	15	(11)
Average	12	(13)		10	(10)
Sainsbury			Sainsbury		
Sainsbury pl	6	(7)	Sainsbury pl	8	(9)
Vimto	5	(9)	Robinsons	11	(12)
Robinsons	9	(8)	OB	12	(13)
OB	8	(10)	RB	9	(13)
			Kia-Ora	13	(13)
Average	7	(9)		11	(12)
Overall Average	10	(11)		11	(11)

Note: average 24 week base used in fitting the Dirichlet model

Each of the three store's private labels are also closely predicted by the model; Sainsbury (Lancashire) 6 (7), Tesco 8 (8), Sainsbury 8 (9). The close fit means that there are no other differences in this respect after having allowed for their market shares. The reason the Tesco private label purchase rate is

higher than the Sainsbury (Lancashire) rate is because it has a lower in-store market share. Research has shown buyers of items with small market shares have the widest repertoires (Ehrenberg 1972, 1988).

Share Of Local Requirements

The difference between w (Table 6.2) and w_p (Table 6.9) shows that most consumers buy more than one item of Fruit Squash even within the same store chain. For example, of the 8 Fruit Squash (Table 6.9) purchases made by Tesco private label buyers, an average of 5.4 (Table 6.2) are of the Tesco private label. The remaining 2.6 are of other brands in the store. The proportion of product field purchases devoted to one item is higher within the store than we found for product field purchasing in section 4.2d (page 107). This is because when analyses are confined to one store chain, buyers purchases at other chains are excluded.

The share of all Fruit Squash purchases given to each item is the share of requirements, derived from the average purchase frequency of a given item (w) as a proportion of their total product field purchase rate (w_p). However, in these analyses purchases are restricted to within individual store chains, so it is essentially a "local share of requirements ratio".

We show below that the consistent discrepancy in chapter 4 (Table 4.15 page 111) which resulted from the high private label purchase rate is no longer evident. Having made allowances for the population at risk, we can examine the local share of requirement ratio further.

The fit of the model across the 4 stores is on average close despite some stores offering private labels and KwikSave being a branded operation (Table 6.10). There are some deviations which distort the overall average; in particular, the three small brands in Sainsbury (Lancashire) and two smaller brands in Tesco. These deviations are not systematic and so they say nothing in general about small brands. Once they are excluded, the fit of the model for the overall average is 51% (49%) in Lancashire and 43% (43%) in London. Each store's private label is closely predicted by the model. This means that differences are mainly due to market shares.

Table 6.10 : Share Of Local Requirements Ratio Within Store Chains For Fruit Squash (48 Weeks)

Item	w/wp		Item	w/wp	
	O	T		O	T
LANCASHIRE			LONDON		
KwikSave			Tesco		
Robinsons	55	(55)	Tesco pl	68	(65)
Vimto	54	(45)	Quosh	38	(39)
GeeBee	42	(32)	Robinsons	31	(37)
Sunland	34	(31)	[RB	19	(30)]
Kia Ora	14	(27)	[OB	19	(30)]
Average	40	(37)		46	(47)
Sainsbury			Sainsbury		
Sainsbury pl	61	(60)	Sainsbury pl	76	(75)
[Robinsons	50	(31)]	Robinsons	36	(34)
[Vimto	52	(25)]	OB	19	(28)
[OB	17	(22)]	RB	39	(28)
			Kia-Ora	26	(28)
Average	61	(60)		39	(39)
Overall Average	51	(49)		43	(43)

Note : average 24 week base used in fitting the Dirichlet model;
[] excluded from the average

Across 14 stores we find that the share of requirements ratio for both brands and private labels is on average slightly higher than predicted. Though the difference is small, 2 and 6 units respectively, it is more consistent for private labels than brands (Table 6.11). Indeed only the Coop Fabric Conditioner (London) share of requirement for private labels is lower than predicted, whereas six brands are below. The average brand buyer devotes 42% (40%) of his purchase repertoire to a brand, as compared to the average private label buyer devoting 67% (61%) to the average private label. The reason ratios are higher for private labels than brands is because the former have a higher

average market share.

Private labels have a slightly higher local share of requirement ratio than predicted because of a high w and/or a low rate of product field buying. However, the cause is not systematic and so it is difficult to draw any conclusions from the result.

There are no systematic differences in the share of requirement attracted by each store's private label. All attract a slightly higher share of their buyers requirements than is predicted. However, the private label buyer of Fabric Conditioner in Sainsbury (Lancashire) devotes 93% of her purchase repertoire to the Sainsbury private label as compared to (79%) predicted. This is a large discrepancy due largely to a high purchase frequency (Table 6.3) combined with a low product purchase rate (Table 6.9). However the size of the discrepancy is unusual and it does not generalise further.

Table 6.11 : Share Of Local Requirements Ratio For The Average Brand And Private Label Within Store Chains (48 weeks)

		Brands		Private Labels	
		O	T	O	T
Fruit Squash					
London	Sainsbury	30	(30)	76	(75)
	Tesco	27	(34)	68	(65)
	Coop	24	(23)	80	(67)
Lancashire	KwikSave	40	(37)	*	*
	Sainsbury	40	(26)	61	(60)
	Tesco	39	(27)	50	(42)
	Coop	39	(26)	55	(44)
Average		34	(29)	65	(59)
Fabric Conditioner					
London	Sainsbury	41	(48)	68	(61)
	Tesco	47	(57)	56	(55)
	Coop	45	(46)	50	(52)
Lancashire	KwikSave	59	(53)	*	*
	Sainsbury	43	(29)	93	(79)
	Tesco	65	(66)	76	(74)
	Coop	50	(53)	64	(56)
Average		50	(50)	68	(63)
Overall Average		42	(40)	67	(61)

Note : average 24 week base used in fitting the Dirichlet model; * means that no private labels are available in the store.

The share of requirements ratio shows how the average buyer apportions his purchases between one item and the rest of the product field. However, some buyers are 100% loyal whilst others have a repertoire of items from which they can choose. We now examine the variation around the average to determine

whether there are any other differences in accordance with the presence of private labels. We begin with sole buying and then move on to duplicate buying.

Incidence And Rate Of Sole Buying

Sole buying analyses tend to use small sample bases. This is because we are examining those buyers who are 100% loyal in an individual store chain in 48 weeks. For example, the 5% of KwikSave Kia-Ora sole buyers (Table 6.12) refers to just one person. Therefore, estimates for the majority of small items are deviant. However, though there are many deviations of this kind, they are not consistent in either their direction or size, and so do not tell us anything about small brands or private labels. Thus sample sizes of below 15 buyers are excluded from the averages. This limitation should be borne in mind in interpreting the results.

We first examine whether sole buying patterns in stores with private labels differ from KwikSave and then compare each store's private label.

On average patterns of sole buying are similar in stores with private labels to those in KwikSave (Table 6.12). The incidences and rates of sole buying tend to be higher than predicted in all four stores. For example, in KwikSave 36% (32%) make 4.8 (3.7) purchases as compared to in Tesco stores with 43% (36%) making 3.3 (3.1) purchases (Table 6.12). Furthermore, individual store's private labels are bought much like the brand leader in KwikSave. This means that the presence of a private label within the store does not attract more sole buying loyalty despite offering something unique to the store.

Table 6.12 : Incidence And Rate Of Sole Buying Within Store Chains For Fruit Squash (48 Weeks)

Item	bs		ws		Item	bs		ws	
	O	T	O	T		O	T	O	T
LANCASHIRE					LONDON				
KwikSave					Tesco				
Robinsons	40	(36)	5.6	(4.0)	Tesco pl	49	(46)	3.9	(3.7)
Vimto	32	(28)	4.0	(3.3)	Quosh	37	(26)	2.6	(2.4)
[GeeBee	27	(21)	2.7	(2.6)]	[Robinsons	24	(25)	2.3	(2.3)]
[Sunland	18	(21)	4.9	(2.5)]	[RB	0	(24)	0	(2.2)]
[Kia Ora	5	(18)	1.0	(2.3)]	[OB	7	(20)	1.0	(2.0)]
Average	36	(32)	4.8	(3.7)		43	(36)	3.3	(3.1)
Sainsbury					Sainsbury				
Sainsbury pl	67	(38)	3.2	(2.1)	Sainsbury pl	61	(58)	6.4	(5.4)
[Rob	17	(20)	2.0	(1.4)]	Rob	17	(21)	3.7	(2.4)
[Vimto	54	(17)	2.9	(1.3)]	[OB	9	(17)	1.0	(2.1)]
[OB	50	(15)	1.0	(1.3)]	[RB	35	(17)	2.9	(2.1)]
					[Kia-Ora	9	(17)	6.0	(2.1)]
Average	67	(38)	3.2	(2.1)		39	(40)	5.1	(3.9)
Overall Average	52	(35)	4.0	(2.9)		41	(38)	4.2	(3.5)

Note : average 24 week base used in fitting the Dirichlet model; [] excluded from the average because sample less than 15 buyers

Each store's private label attracts more sole buyers who make more purchases than predicted. In this sense each store's private label is bought much like any other, once market share differences have been allowed for; the Tesco private label has 49% (46%) sole buyers who make 3.9 (3.7) purchases; Sainsbury (London) has 61% (58%) of sole buyers making 6.4 (5.4) purchases.

However, the Sainsbury (Lancashire) private label has a much higher incidence of sole buying than is predicted, 67% (38%). Though the size of the deviation is unusually large in comparison to the others, it does not generalise to other

private labels, nor other Sainsbury private labels as we show below.

In Table 6.13 sole buying results are generalised. All items have been retained in the average calculation because though small sample results are deviant, they occur in all store chains and do not change the conclusion.

In chapter 4 we found that the rate of buying by sole private label buyers was much higher than for the average brand and than the model predictions (Table 4.19 page 116). However, it was difficult to determine whether this was due to the mis-specified population at risk or some other reason. Within-store analyses enable us to examine the issue further with minimal population at risk interference. We show below that there are still differences between brands and private labels in respect of sole buying even when the population at risk is more correctly specified.

The incidence of sole buying for private labels across the two product fields is on average higher than predicted, 60% (47%), a difference of 13 points (Table 6.13). By contrast, the incidence for brands is 35% (31%), a 4 point difference. On all 12 occasions, the incidence of sole buying by private label buyers is higher than predicted. Though this also occurs for some of the brands, especially those in the Lancashire region, the difference is not systematic and smaller than for private labels. This suggests that private labels attract a higher incidence of sole buying than the average brand and than is predicted by the model.

Rates of buying by sole buyers are also higher than predicted (Table 6.13). Private label sole buyers make an average 3.5 (2.9) purchases and sole brand buyers make 2.3 (2.2). In chapter 4 the observed rate of sole buying was some 80% higher than predicted (Table 4.19 page 116). When the population at risk is more correctly specified, the rate is still 20% higher. The comparison is not exactly the same because some of the smaller stores are excluded from the within store analyses shown in Table 6.13, whereas in chapter 4 the full data set was shown. However, within these smaller store chains, the results are similar.

Only one private label has a rate of sole buying below the predicted level Fabric Conditioner (London) Coop as compared to half the brand figures.

Therefore, on average both the incidence and rates of sole buying by private label buyers are higher than for the average brand and than is predicted by the model.

Table 6.13 : Incidence And Rate Of Sole Buying For The Average Brand And Private Label Within Store Chains (48 weeks)

		Brands		Private Labels	
		bs	ws	bs	ws
Fruit Squash					
London	Sainsbury	18 (18)	3.4 (2.2)	61 (58)	6.4 (5.4)
	Tesco	17 (23)	1.5 (2.2)	49 (46)	3.9 (3.7)
	Coop	31 (15)	2.3 (1.6)	63 (45)	4.2 (2.7)
Lancashire	KwikSave	24 (24)	3.6 (2.9)	* *	* *
	Sainsbury	40 (17)	2.0 (1.3)	67 (38)	3.2 (2.1)
	Tesco	27 (17)	2.0 (1.6)	47 (26)	2.2 (2.0)
	Coop	21 (16)	2.2 (1.4)	53 (26)	2.3 (1.9)
Average		25 (19)	2.4 (1.9)	57 (40)	3.7 (3.0)
Fabric Conditioner					
London	Sainsbury	23 (38)	3.2 (2.7)	52 (50)	3.8 (3.2)
	Tesco	42 (48)	1.9 (2.4)	58 (46)	2.4 (2.3)
	Coop	25 (42)	1.8 (2.3)	61 (45)	2.3 (2.4)
Lancashire	KwikSave	45 (39)	3.1 (2.6)	* *	* *
	Sainsbury	64 (23)	1.6 (1.1)	73 (63)	2.5 (1.9)
	Tesco	66 (61)	2.6 (3.6)	72 (69)	5.7 (3.9)
	Coop	42 (45)	2.0 (2.2)	55 (47)	2.4 (2.3)
Average		44 (42)	2.3 (2.4)	62 (53)	3.2 (2.7)
Overall Average		35 (31)	2.3 (2.2)	60 (47)	3.5 (2.9)

Note : average 24 week base used in fitting the Dirichlet model; * means there are no private labels available in the store.

Though there is variation by each private label, it is not systematic. This means that private labels generally attract more sole buyers who buy more frequently than the average brand and than is predicted from theory.

Private labels attract more sole buying loyalty when they are the within-store brand leader, and when they are not. However, the KwikSave brand leader also attracts more loyalty, but this does not occur for other brand leaders (Table 6.14). For example, the KwikSave brand leader, Robinsons, has 40% (36%) sole buyers who make 5.6 (4.0) purchases, yet the brand leader in Coop (London), Comfort, has 50% (51%) sole buyers making 2.5 (2.6) purchases.

Therefore, from these limited analyses, it seems that in stores without private labels, the brand leader attracts more sole buying loyalty than its market share warrants. But when a private label is available, be it the brand leader or otherwise, it attracts more sole buying loyalty and brands fall in line with the theoretical predictions whether or not they are brand leader.

Table 6.14 : Incidence And Rate Of Sole Buying For Within-Store Brand Leaders (48 weeks)

Store	Product Field Region	Brand	bs		ws	
			O	T	O	T
KwikSave	Fruit Squash Lan	Robinsons	40	(36)	5.6	(4.0)
	Fabric Cond Lan	Comfort	74	(51)	4.4	(3.2)
Coop	Fabric Cond Lon	Comfort	50	(51)	2.5	(2.6)
	Fabric Cond Lan	Comfort	51	(51)	2.7	(2.5)
Tesco	Fabric Cond Lon	Comfort	49	(48)	2.4	(2.4)

Summary Of Sole Buying Results

In chapter 4 we found that private label sole buyers were some 80% more frequent buyers than the average brand and than was predicted from theory, though their incidences were in line with the theory. Rates of buying by sole brand buyers were also some 20% higher than predicted. However, we could not determine whether these results were because of the mis-specified population at risk or some additional result. By examining purchasing within store chains, we shown that even when the population at risk is more correctly specified, differences between brand and private label sole buying patterns still remain.

Both the incidence and rate of sole buying are higher for private labels than

for the average brand, and than is predicted by the model. Rates of buying by sole buyers are on average over 20% higher than predicted, and the incidence is nearly 30% higher. The size of the discrepancy for rates of sole buying is smaller than was found in chapter 4; but the difference in the incidence of sole buying is a new result which did not show through in chapter 4.

This suggests that some of the chapter 4 discrepancy in sole buying rates was because of the mis-specified population at risk ie a repercussion from the high private label w. However, why this showed through in the rate of sole buying and not in both its incidence and rate is unclear. We discuss this in more detail in chapter 9. Once the population is correctly specified, we find that private labels attract more sole buyers who buy more often than the average brand and than is predicted from theory.

However, in the two data sets examined, the brand leader in KwikSave also attracts more sole buying loyalty than predicted. But this does not occur for any other brand leader examined. This means that stores with private labels have similar patterns of sole buying behaviour to KwikSave. The presence of a private label in the store does not affect buying patterns other than some substitution effects as it is included in buyers repertoires.

When a private label is available, whether it be the within-store brand leader or not, it attracts more sole buying loyalty than is predicted by the model. The same does not occur for brands, except for the KwikSave brand leader. Brands in other stores attract the level of sole buying which is predictable given their market shares. We discuss reasons for this result in chapter 9. For example, it may be a result of shelf space allocation and position rather than specifically to do with the item leader per se.

Each store's private label attracts more sole buying loyalty than predicted. There is some variation between private labels in this respect, but it is not systematic. There is no indication for example, that the Sainsbury private label consistently benefits from more sole buying loyalty than any other private label.

Patterns of sole buying which were discussed in Chapter 4 (section 4.2d page 112) are not so clear in the within-store analyses. However, even in Chapter 4, the Double Jeopardy pattern is unclear. This suggests that the Dirichlet model is slightly deviant when it comes to predicting sole buying patterns.

We examine loyalty issues again in the following chapter and this is discussed further in chapter 9.

The complement to sole buyers are duplicate buyers who switch between different items and have a repertoire of goods. We have just shown that private labels attract somewhat more sole buying loyalty than predicted. This should have repercussions on duplicate buying, which is examined next.

Incidence And Rate Of Duplicate Buying

In the previous section it was shown that an average of 50% of buyers remain completely loyal to one particular item within the store in 48 weeks. This means the rest have also bought other items of Fruit Squash, even from within the same store chain. In this section the discussion centres on which others are also bought and in what proportions. The duplication table which follows enables us to examine how consumers spread their purchases across the product field. Details were given for the well-established patterns of duplicate buying (section 4.2d page 117).

In chapter 4 we showed that brands and private labels were bought interchangeably and much in line with their market shares. The fact that the population at risk was mis-specified did not show through in the duplicate buying analyses. However, given that there are differences in sole buying patterns as outlined in the previous section, this should affect duplicate buying.

Duplication with private labels tends to be lower than predicted, and this does not happen for the brand leader in KwikSave (Table 6.15). This means that buyers of private labels make fewer purchases of other items in the store chain in comparison to brand buyers because more of their purchases are given to the private label. This suggests some heightened loyalty to the individual private label. For example, average duplication with the Tesco private label is 59%, which is below the (70%) predicted; similarly for the Sainsbury (Lancashire) private label, 49% (53%), and Sainsbury (London) 70% (94%).

The latter prediction is slightly distorted by the Duplication law because an item with a high market share multiplied by the Duplication coefficient can in theory exceed 100%. However, within store duplication with the Sainsbury (London) private label is high; on average 70% of buyers also buy the Sainsbury private label. Moreover, duplication by Sainsbury private label buyers with other

items is lower than predicted (reading across the Sainsbury private label row) because they concentrate their purchases on the Sainsbury private label. However, the difference is greater in Sainsbury (London) than Sainsbury (Lancashire). In the latter the average and predicted duplications are much closer.

The main patterns of duplicate buying within the store are similar in stores with and without private labels. Duplication declines with penetration which reflects the fact that large items generally attract more duplicate buyers than do smaller ones. For example, in KwikSave average duplication falls from 53% to 15% (Table 6.15) as penetration falls from 15% to 3% (Table 6.2). The same patterns occurs in the other stores.

There are some exceptions to this general pattern especially for small items. For example, average duplication with Kia-Ora in KwikSave 15% (10%), other brands (OB) in Tesco 20% (13%); and Kia-Ora in Sainsbury (London) which all have a particularly high incidence of duplicate buying given their market shares. These are mainly compensated for by the low duplication with the private labels.

The presence of a private label in the store is not reflected by a difference in the way in which people spread their purchases across the product field. There is a slight tendency for private label buyers to devote more purchases to the private label than to other brands, whereas in KwikSave the same loyalty does not accrue to the brand leader.

Table 6.15: Incidence Of Duplicate Buying Within Store Chains For Fruit Squash (48 weeks)

LANCASHIRE KwikSave						LONDON Tesco					
Item	R	V	G	S	K	T	Q	R	RB	OB	
Robinsons	*	30	14	24	14	Tesco pl	*	28	35	8	15
Vimto	46	*	24	22	16	Quosh	47	*	40	14	21
GeeBee	38	41	*	16	10	Robinsons	56	38	*	16	22
Sunland	61	37	16	*	18	RB	60	60	70	*	20
Kia Ora	67	48	33	33	*	OB	73	60	67	13	*
Average	53	39	22	24	15		59	47	53	13	20
Predicted	51	34	20	20	10		70	45	45	13	13
D = 3.4						D = 6.4					
Deviation	2	5	2	4	5	(11)	2	8	0	7	
Sainsbury						Sainsbury					
Item	S	R	V	O		S	R	O	RB	K	
Sains pl	*	17	18	10		Sains pl	*	26	13	6	8
Robinsons	67	*	17	17		Robinsons	77	*	23	8	18
Vimto	31	15	*	8		OB	76	45	*	12	27
OB	50	20	10	*		RB	52	22	17	*	13
						Kia-Ora	73	55	41	14	*
Average	49	17	12	12			70	37	24	10	17
Predicted	53	15	15	15			94	31	16	12	9
D = 7.5						D = 3.2					
Deviation	(4)	2	3	3		(24)	6	8	2	8	

Duplication coefficients vary from 3.2 to 7.5. These are much higher than found in chapter 4 duplication analyses (section 4.2d page 120) because there is more switching between items within a store chain than in the product field generally.

Across both product fields we find that the low duplication with private labels

is less evident (Table 6.16). Duplication with private label Fabric Conditioner is much as predicted. On average 23% (22%) of buyers duplicate their purchases with the average brand; and 38% (45%) do so with the average private label. So there is only a slight tendency for duplication with private labels to be lower than predicted, which reflects the sole buying results shown earlier. The difference is small but consistent except for Fabric Conditioner, Sainsbury, where the incidence of duplication is slightly higher than predicted.

Table 6.16 : Incidence Of Duplicate Buying For The Average Brand And Private Label Within Store Chains (48 weeks)

		Average Brand	Average pl
Fruit Squash			
London	Sainsbury	22 (17)	70 (94)
	Tesco	33 (29)	59 (70)
	Coop	18 (15)	41 (52)
Lancashire	KwikSave	31 (27)	* *
	Sainsbury	14 (15)	49 (53)
	Tesco	16 (14)	29 (39)
	Coop	17 (15)	43 (57)
Average		22 (19)	49 (61)
Fabric Conditioner			
London	Sainsbury	25 (25)	43 (42)
	Tesco	27 (25)	23 (28)
	Coop	31 (30)	26 (29)
Lancashire	KwikSave	33 (33)	* *
	Sainsbury	11 (11)	26 (25)
	Tesco	19 (19)	21 (23)
	Coop	25 (24)	25 (27)
Average		24 (24)	27 (29)
Overall Average		23 (22)	38 (45)

These results suggest that there is little segmentation between brands and private labels within the store in individual product fields. Though we have shown that private labels attract slightly more sole buying loyalty and therefore less duplicate buying loyalty, the differences are small.

Generally rates of duplicate buying are greater than rates of buying by all buyers. However, in Table 6.17 we find that for larger brands and private labels duplicate buying rates are below rates for all buyers, and the opposite occurs for smaller items. There is no consistent difference between brands and private labels in respect of their duplicate buying rates, nor between each store's private label.

Table 6.17 : Average Rate Of Duplicate Buying Within Store Chains For Fruit Squash (48 weeks)

LANCASHIRE						LONDON					
KwikSave						Tesco					
Item	R	V	S	G	K	T	R	Q	OB	RB	
Robinsons	*	6.5	6.0	5.1	7.1	Tesco pl	*	6.2	9.2	6.7	11.2
Vimto	9.0	*	6.8	6.9	12.1	Robinsons	3.5	*	3.1	3.6	1.7
Sunland	4.1	3.1	*	2.7	3.7	Quosh	3.2	3.1	*	3.0	6.5
GB	4.1	5.1	3.0	*	4.7	OB	2.3	2.6	1.6	*	2.0
Kia Ora	2.4	2.7	2.9	2.6	*	RB	3.3	3.6	1.7	1.0	*
Average	4.9	4.4	4.7	4.3	6.9		2.5	3.1	3.1	2.9	4.3
w	6.0	5.9	3.7	4.2	2.3		5.4	2.8	3.4	2.1	2.8
Sainsbury						Sainsbury					
Item	S	R	V	OB		S	R	OB	RB	K	
Sainsbury pl	*	4.9	2.3	6.2		Sainsbury pl	*	7.1	7.4	7.0	8.0
Robinsons	6.3	*	5.5	15.0		Robinsons	4.2	*	5.7	5.8	4.3
Vimto	2.0	3.0	*	1.0		OB	2.4	2.4	*	1.8	2.8
OB	1.6	1.5	2.0	*		RB	4.2	3.6	2.5	*	5.0
						Kia-Ora	3.7	4.6	5.3	1.0	*
Average	3.3	3.1	3.3	7.4			3.6	4.4	5.2	3.9	5.0
w	3.8	4.7	2.4	1.3			6.7	4.0	2.3	3.4	3.5

There are some high values in Table 6.17. For example, in KwikSave, Vimto buyers who also buy Kia-Ora do so 12.1 times on average. This is due to a small sample base where rates of buying are easily distorted by the behaviour

of a few individuals. Such high values occur in stores with and without private labels, so do not affect the main comparison.

Summary

There are some interesting differences in within-store product field buying patterns between brands and private labels which together could be interpreted as differences in loyalty. The within-store analyses enables us to re-examine product field buying without population at risk effects and so look for "real" private label differences.

Across both product fields, private labels attract a slightly higher share of their buyers requirements than do brands; the difference is small but consistent with a 6 and 2 point difference between the observed and theoretical respectively. However, the reason this occurs is not consistent, resulting from a slightly higher rate of buying and/or a slightly lower rate of product field buying. Because the reason is inconsistent, it is difficult to draw any firm conclusions for the result. However, this does not result in brands being bought any differently from what is predicted from theory. Furthermore, each store's private label is bought in this respect much like any other. We do not find, for example, that the Sainsbury private label consistently attracts a higher share of its buyers repertoire than any other one.

The main results from this section concern sole buying patterns. In chapter 4 we found that private label sole buyers had a much higher rate of buying than predicted, and than the average brand. When the population at risk is correctly specified, the difference still remains, though it is smaller than was found in chapter 4 and occurs in both the incidence and rate of sole buying whereas in chapter 4 it occurred predominantly in the incidence of sole buying. This suggests that some of the chapter 4 difference is a population at risk effect, the rest is additional and says something about private label loyalty.

We find that private labels have both a higher incidence and rate of sole buying than the average brand and than is predicted by the model. On average the incidence of sole private label buying is 60% (47%), a 17 point difference, compared to 35% (31%), a 4 point difference for the average brand. Similarly for the rate of sole buying; the average rate of sole private label buying is 3.5 (2.9), and for brands the rates are 2.3 (2.2). This occurs when the private label is the within-store item leader and when it is not, but only occurs for brands

when they are the within-store brand leader, and where no private label is available. Each store's private label is similar in this respect. This suggests that private labels attract more sole buying loyalty than the average brand irrespective of their position in the store.

The incidence and rate of duplicate buying by private label buyers is slightly lower than predicted. However, the difference is small and occurs predominantly for Fruit Squash purchasing. Because private labels attract more sole buying loyalty than brands, they have fewer duplicate buyers. Again this result supports the idea that private labels attract more loyalty from their buyers than the average brand.

Though these results suggest private labels attract slightly more loyalty than a comparable brand and than is predicted from theory, the same also occurs for the brand leader in KwikSave. We discuss why this might occur in chapter 9.

However, despite these minor differences, the presence of a private label in the store does not seem to affect brand buying patterns. Most brands are bought in stores where private labels are available in the same way as they are in KwikSave. It is only with brand leaders where we have noted some differences.

These results have only been generalised over four data sets ie two product fields and two regions. This limitation should be borne in mind in interpreting the results. However, the product fields are quite different in nature and the two regions have different retail compositions which enhances the reliability of results somewhat.

6.4 SUMMARY AND CONCLUSIONS

In chapter 4 it was difficult to determine which results were due to the mis-specified population at risk and which were additional. Analyses at the within-store level enable us to examine brand and private label purchasing without population at risk effects and also to compare purchasing within different store chains.

Bearing in mind the three objectives of this chapter. First, we show that buying patterns in stores with private labels are much the same as in KwikSave, and there are no consistent differences in accordance with the

presence of private labels. Secondly, we show that each store's private label is bought much like any other once market share differences have been allowed for. Thirdly, we show that there are still some differences between brands and private labels in respect of sole buying in particular, once the population at risk is correctly specified.

Results from the within store analyses show that on the whole private labels are bought much like brands. As far as the number of people buying, and the rate at which they buy; and buying from one time period to the next, private label buying patterns are similar to patterns of brand buying behaviour. Both are bought largely in line with their market share levels and as such can be described by the stochastic models.

However, when these measures are disaggregated, there is some evidence to suggest that private labels attract slightly more loyalty than the average brand, and than is predicted from theory. These differences are small but consistent. We have shown this by a variety of measures including the local share of requirements ratio and sole and duplicate buying. The fact that all measures support this basic result is important.

More detailed results are now summarised starting with where private label purchase behaviour is similar to brands, and then elaborating on the differences.

- * The presence of private labels in a store is not reflected by a difference in the number of people buying the product field, nor the rate at which they buy from what is predicted from theory. People buy in stores with private labels in much the same way as they do in KwikSave. Furthermore, each store's private label is bought in line with the theoretical predictions as far as penetration and purchase frequency are concerned.
- * There is no sizeable difference in period to period buying behaviour within a store offering a private label and one that does not. The fact that a store offers a private label does not mean, for example, that the private label or brand obtains a higher level of repeat buying than occurs in a store with no private labels. The existence of the private label does not affect the way people buy other brands in the store over time, over

and above some substitution with the private label as it becomes part of the buyers repertoire. Each store's private label is similar in this respect.

- * The purchase frequency distributions are similar for stores with and without private labels on average. Buyers in Sainsbury and Tesco stores where private labels are available, distribute their purchases within the store in the same way as do buyers in KwikSave stores. The observed distribution was found to be slightly more skewed towards light buyers at the expense of medium and heavy buyers, and this occurred for most items in the product field. Furthermore, individual private labels (Sainsbury excluding) also follow the same patterns as their branded counterparts.
- * The above measures of buying behaviour are much in line with the model predictions. There were some consistent deviations though with the incidence of repeat buying and the purchase frequency distribution. However, these occur similarly for all items in the product field so do not interfere with the main comparison. The product field deviation is taken into account before examining other differences between brands and private labels.
- * These results lend further support to the population at risk explanation which largely accounts for the high private label purchase frequency identified in chapter 4. When analyses are restricted to a common population at risk ie individual store chains, the average purchase frequency deviation is no longer consistently evident.
- * Purchasing at the within-store level largely follows that in the market place more generally and as such can be described by the same stochastic models.

Even when the population at risk is correctly specified, there are still some differences between brand and private label purchasing patterns. These are interpreted as "real" private label results which we detail below.

- * A particularly interesting result is that private labels are so successful and achieve such high market shares within the store. When they are available, they tend to be the within-store brand leader. But once these

market share differences are allowed for, they are bought much like any other brand leader as far as penetration and average purchase frequency is concerned. So there is nothing special in the way the private label is bought, but in the market share level it achieves.

- * When private labels have a high share of the product field, this is a result of the contribution of many stores' private labels. So a private label with a high market share like Fruit Squash, is not just a result of Sainsbury and Tesco stores having high shares, but other retailers also have a similarly high share. Indeed, there are no "small" private labels in the two product fields examined. The smallest share is 21%. This either means that all private labels achieve a sizeable market share or that if they do not, they are delisted.
- * From the product field analyses we find evidence to suggest that private labels attract slightly more loyalty than the average brand and than is predicted from theory.
- * Private labels have a slightly higher local share of requirements ratio than do brands within a store chain. However, the cause of this is not systematic so it is difficult to draw interpretations from it.
- * Private labels have a higher incidence and rate of sole buying than the average brand and than is predicted from the model. Rates are some 20% higher and the incidence is some 30% higher than predicted. The same directional discrepancy also exists for brands, but it is smaller and less consistent than for private labels. However, this also occurs for the brand leader in KwikSave, but not for any other brand leader. So it seems that private labels attract this "extra" loyalty but in their absence, the brand leader does.
- * The incidence and rate of duplicate private label buying is slightly lower than predicted. The difference is mainly in Fruit Squash though as Fabric Conditioner duplicate buying is much in line with the predicted level. Because private labels attract slightly more sole buyers they tend to have fewer duplicate buyers.
- * We find these differences are similar for each stores' private label. The

share of requirements ratio for example, varies unsystematically across the private labels. So we do not find that the Sainsbury private label attracts a higher share of its buyers repertoire than the Tesco private label. Similarly for sole buying patterns.

- * However, the Sainsbury private label is particularly successful in the market share level it achieves within the store chain. Neither the brand leader in KwikSave, nor those in other stores achieve the same market share as the Sainsbury private label. This has on average a 60% share across both product fields. Even in Fabric Conditioner, where private label shares are lower, it still achieves a 58% share on average. There is also some evidence that it attracts slightly more medium and heavy buyers than any other item because its purchase frequency distribution was not so positively skewed as for other items. These issues are discussed in more detail in chapter 9.

These latter points are particularly interesting given retailers objectives in offering private labels (Chapter 1 page 24). Together they support the idea that private labels attract slightly more loyalty from their buyers than the average brand. This is so even after allowing for population at risk and market share differences.

By offering a private label, the retailer should gain from this "extra loyalty". Furthermore, this extra loyalty is not to the detriment of the store's brands, it is additional. However, this occurs for all retailers' private labels. So though one retailer is gaining from this, so are all the others. It is unlikely that any competitive advantage arises. We examine differences between loyalty to specific store's private labels in more detail in the following chapter.

So far these findings are generalisable over two product fields and regions, and for a selection of store chains. They are not dependent on the level of private label in the store or region under analysis, but occur for private labels generally. Furthermore, they apply to all stores' private labels. However, only two product fields have been examined so results need to be generalised further to ensure their reliability.

We have shown there is evidence to suggest that private labels attract slightly more loyalty than the average brand, but that on the whole brand and private

label purchasing within individual store chains is similar and much in line with the theory. We now examine loyalty to private labels generally and to specific store's private labels by analysing purchase behaviour across two product fields. This is a new area of work and so is largely exploratory in nature.

CHAPTER 7 : HOW PEOPLE BUY PRIVATE LABELS ACROSS TWO PRODUCT FIELDS

7.1 Introduction**7.2 Data Used In The Analyses****7.3 How People Buy Any Brand And Any Private Label Across Two Product Fields****7.3a Penetration And Average Purchase Frequency Across Two Product Fields****7.3b Product Purchase Rate And Share Of Requirements Ratio Across Two Product Fields****7.3c Incidence and Rate Of Sole Buying Across Two Product Fields****7.3d Incidence and Rate Of Duplicate Buying Across Two Product Fields****7.3e Summary****7.4 How People Buy Individual Items Across Two Product Fields****7.4a Penetration and Average Purchase Frequency Across Two Product Fields****7.4b Product Purchase Rate and Share Of Requirement Ratio Across Two Product Fields****7.4c Incidence and Rate Of Sole Buying Across Two Product Fields****7.4d Incidence and Rate Of Duplicate Buying Across Two Product Fields****7.4e Summary****7.5 Summary And Conclusions**

7.1 INTRODUCTION

The analyses in this chapter comprise a new area of research and so are largely exploratory in nature. So far, we have examined the purchasing of brands and private labels in a selection of product fields one at a time. In chapters 4 and 5, we concentrated on purchasing behaviour in the market place generally; then in chapter 6, on purchase behaviour within individual store chains. In this chapter we examine how people buy brands and private labels across two product fields. This is important for two main reasons.

We have already shown that even when a more relevant population at risk is specified, there are still some differences which suggest that private labels attract slightly more sole buying loyalty than the average brand. By examining purchasing across two product fields we can focus on loyalty to specific store's private labels, and to private labels generally. This is essentially a first step towards an examination of private label proneness. For example, we ask do those who buy private labels in one product field also buy them in another? Are people who buy certain store's private labels more likely to buy the same private label in another product field?

Secondly, this enables us to determine whether the models describe purchasing across two product fields, and whether this is so for both brands and private labels. This is a new area of research with much potential for development by linking purchase behaviour across many product fields so as to capture peoples' wider shopping repertoires. Retailers are interested in what constitutes store traffic and linking purchase behaviour across many product fields provides such information. This is important when planning for say merchandising where identifying which products attract the majority of shoppers means they can be placed strategically around the store. Information on the interaction between many product fields and their buyers would be valuable for such decisions. The leap between one product field and the typical basket of groceries is a large one, but this chapter aims to take a first step in that direction.

The Dirichlet model is again used as our norm because it has been extensively generalised. Furthermore, in chapters 4 to 6 we have shown that once the relevant population at risk is used, it also describes private label purchase behaviour. We can therefore build on these foundations and examine multi-product field buying.

Chapter 7 comprises 4 parts. In section 7.2 we explain the data used in the analyses. In section 7.3 buying behaviour for any brand and private label across the two product fields is examined; this includes penetration and purchase frequency and then product field buying. In section 7.4, buying behaviour for individual items across both product fields is examined in the same way as in section 7.3. Finally, in section 7.5 results are summarised and some early conclusions are drawn.

7.2 DATA USED IN THE ANALYSES

In each region, data for Fruit Squash and Fabric Conditioner has been merged. This was undertaken in such a way that household identities have been preserved so that purchasing across the two product fields relates to the same people. In section 7.3 there are two data sets, London and Lancashire, each with a grouping for brands and private labels. In section 7.4 only the London data set is examined, and each brand and private label in each product field is itemised. These are explained in more detail below.

In section 7.3, there are 4 mega-items in each region; Fruit Squash brands, Fruit Squash private labels, Fabric Conditioner brands and Fabric Conditioner private labels. This means we are treating Fruit Squash and Fabric Conditioner as one large combined product field with four items from which to choose. The population at risk problem is overcome by aggregating individual private labels into one group. However, the same occurs for brands which means that the opportunity to buy the brand is still greater than the mega-private label.

In section 7.4, there are 14 items comprising brands and private labels from both product fields in the London region. This means we are treating London as one large combined product field where consumers have 14 items from which to choose their Fruit Squash and Fabric Conditioner purchases. In this case private labels still suffer from a mis-specified population at risk. So results are also shown for purchasing across two product fields within Sainsbury and Tesco stores. In this instance, the population at risk differences are overcome and we can interpret the results accordingly.

Fewer analyses are shown than in chapters 4 and 6 because we focus on private label proneness. First, we examine the components of the sales equation as this is a means of determining whether the models describe purchase behaviour across two product fields. Then we examine product field

buying to determine whether there are any signs of general (to any private label) or specific (to a certain store's private label) private label proneness.

The objectives of this chapter are threefold; to determine whether the Dirichlet model describes how people buy across two product fields; whether there are any differences in the way in which people buy brands and private labels; and whether there is any evidence of general and/or specific private label proneness.

7.3 HOW PEOPLE BUY ANY BRAND AND ANY PRIVATE LABEL ACROSS TWO PRODUCT FIELDS

7.3a Penetration And Average Purchase Frequency Across Two Product Fields

The patterns discussed in chapters 4 and 6 (section 4.2a and 6.3a pages 85 and 179) are also found in purchasing across two product fields (Table 7.1). For example, large items not only have more buyers, but they buy them more often than buyers of smaller brands. In London, penetration falls from 55% to 30%, and average purchase frequency falls from 7.8 to 3.9.

The reason the Double Jeopardy pattern exists when the two data sets are merged is because the rates of product field buying for both are similar. If Baked Beans had been combined with Fruit Squash, the results would not have followed this pattern.

The Fruit Squash (London) grouping deviates from the Double Jeopardy pattern because the brand purchase rate is lower than for private labels despite the latter having a slightly higher penetration. However, this does not generalise to the other product field or region. Nevertheless, because this data set has been the focus of chapter 4 analyses, some comment is required.

In the within-store analyses, the high private label w was not evident for Fruit Squash (London) though it still showed through slightly in the mega-private label data set. The fact that despite overcoming the population at risk problem, the high private label purchase frequency still shows through on this occasion may be due to the extent of this particular discrepancy in chapter 4. However, because the other private label group purchase rates are consistently below the theoreticals when the adjustment is made this means that once the population at risk differences are overcome, the consistently high private label

w is no longer evident. Instead we find that on some occasions it is high and on others it is lower than predicted.

The fit of the model is close on average in both regions. There are slightly more buyers who buy less often than is predicted from theory. On average 48% (45%) of people buy the four items and do so 6.4 (7.0) times.

This means that people buy any brand and any private label in two product fields in much the same way as they do in one. Also, purchase behaviour in two product fields can largely be described by the Dirichlet model.

Table 7.1 : Penetration And Average Purchase Frequency For Any Brand And Private Label Across Two Product Fields (48 weeks)

London

Item	Market Share	O	b T	O	w T
Squash brand	29	55	(52)	6.2	(6.6)
Squash pl	36	53	(59)	7.8	(7.1)
Fab brand	25	49	(47)	5.9	(6.2)
Fab pl	10	30	(23)	3.9	(5.2)
Average	25	47	(45)	6.0	(6.3)
Lancashire					
Item	Market Share	O	b T	O	w T
Squash brand	55	71	(79)	11.7	(10.5)
Fab brand	24	57	(49)	6.3	(7.3)
Squash pl	16	44	(37)	5.7	(6.7)
Fab pl	5	23	(14)	3.6	(5.8)
Average	25	49	(45)	6.8	(7.6)
Overall Average	25	48	(45)	6.4	(7.0)

Note : average 24 week base used in fitting the Dirichlet model.

Private labels with 46% of the London market and 21% in Lancashire follow the regular patterns. They attract a similar buying profile in respect of the numbers buying and that rate at which they buy. They are bought much in line with their market shares.

In light of our population at risk explanation, one might expect private labels to still have a higher purchase rate than predicted. This is because in Chapter 5 we found private labels suffered in two related ways; they were not as widely available, and suffered from a lower opportunity to buy than for the average brand. By grouping private labels, the opportunity to buy is equivalent to that for any large brand. But by grouping brands, the opportunity to buy is much higher than the mega-private label because there are many brands to choose from and only one private label on each purchase occasion. This means the population at risk will be correctly specified, but the opportunity to buy differs.

The fact that the private label purchase rate is not consistently higher than predicted suggests that differences in the opportunity to buy alone are not sufficiently important to show through in the results and are probably reflected in the market shares anyway. Opportunity to buy differences may be overcome to some extent by the fact that people have a repertoire of stores from which to choose.

We now examine how people spread their purchases across both product fields so as to examine general private label proneness.

7.3b Product Purchase Rate And Share Of Requirements Ratio Across Two Product Fields

Here we examine how many purchases of the combined product fields buyers of each of the four groups make, and what share of their purchases are given to each of the four categories.

As detailed in chapter 4 (section 4.2d page 107), there are some regular patterns of product field purchase behaviour; product field rates are usually similar within a given time period; differences in the share of requirements ratio are largely the result of differences in average purchase frequency; and items with larger market shares receive a higher share of their buyers needs than do smaller ones.

On the whole the same patterns occur across both product fields (Table 7.2). wp varies little in each region and is closely predicted by the Dirichlet model; in London buyers make on average 17 (16) purchases of the four categories, in Lancashire they make 19 (19). The share of requirements ratio varies between the four groupings largely in accordance with market share, and is on average slightly below the model predictions due to the low average purchase frequencies (Table 7.1). For example, in London buyers devote 36% (40%) of their purchases to one grouping, in Lancashire they devote 36% (41%) on average.

Private labels largely fall in line with these patterns. Their product purchase rates are similar to that for brand groupings and closely predicted by the model. They satisfy between 20% and 45% of their buyers requirements so are no more loyal than brand buyers in this respect. In chapter 6, it was found that private labels attracted a slightly higher share of their buyers local repertoire, (section 6.3d page 207) but there are no signs of this result here.

Product purchase rates and share of requirement ratios for brands and private labels in two product fields are similar to those in one, and on the whole buying patterns are closely described by the Dirichlet model. The number of product field purchases and the share of requirements ratio are similar for brands and private labels.

Table 7.2 : Product Purchase Rate And Share Of Requirement Ratio For Any Brand And Private Label Across Two Product Fields (48 weeks)

London				Lancashire					
Item	wp		w/wp		Item	wp		w/wp	
	O	T	O	T		O	T	O	T
Squash brd	16	(16)	38	(42)	Squash brd	19	(17)	61	(61)
Squash pl	17	(15)	45	(46)	Fab brd	17	(19)	36	(39)
Fab brd	16	(16)	38	(39)	Squash pl	22	(19)	26	(35)
Fab pl	17	(17)	23	(31)	Fab pl	18	(20)	20	(29)
Average	17	(16)	36	(40)		19	(19)	36	(41)

Note : average 24 week base used in fitting the Dirichlet model
We now examine sole buying patterns across two product fields.

7.3c Incidence And Rate Of Sole Buying Across Two Product Fields

In chapter 4 (section 4.2d page 112), regular patterns of sole buying behaviour were outlined. The results below show the proportion of buyers who remain 100% loyal to one of the four categories in 48 weeks, and the number of purchases made by these buyers in the same time period.

On average we find that less than a fifth of buyers remain 100% loyal in 48 weeks, much in line with the predicted level (Table 7.3) and similar to that found for product field buying in chapter 4 (Table 4.17). There are some large but inconsistent deviations in both the incidence and rate of sole buying. The fit of the Dirichlet for sole buying is poor at the individual level and this has also been found in studies undertaken in-house. In Table 7.3, Fabric Conditioner brands in both regions have a much higher incidence of sole buying than predicted, 21% (14%) and 23% (12%) in London and Lancashire respectively. For the remainder, the incidence is more closely predicted, but the rate of sole buying tends to be low. These deviations occur for brands and private labels so do not affect the main comparison.

In chapter 6, (Table 6.13) we showed that individual private labels attracted more sole buying loyalty than the average brand, and than was predicted by the model. (Though this was also so for the brand leader in KwikSave.) However, when all private labels are combined and buying across two product fields is examined, sole buying loyalty is similar to that for brands. This suggests that the "extra" loyalty identified earlier is to specific store's private labels. By grouping them all together the effect does not show through.

Table 7.3 : Incidence And Rate Of Sole Buying For Any Brand And Private Label Across Two Product Fields (48 weeks)

London					Lancashire				
Item	bs		ws		Item	bs		ws	
	O	T	O	T		O	T	O	T
Squash brd	15	(15)	3.9	(5.6)	Squash brd	21	(28)	8.6	(10.7)
Squash pl	19	(18)	5.8	(6.2)	Fab brd	23	(12)	4.2	(7.6)
Fab brd	21	(14)	5.3	(5.3)	Squash pl	10	(10)	5.0	(6.9)
Fab pl	10	(9)	3.0	(4.3)	Fab pl	9	(7)	4.2	(6.0)
Average	16	(14)	4.5	(5.4)		16	(14)	5.5	(7.8)
Overall Avge	16	(14)	5.0	(6.6)					

Note: average 24 week base used in fitting the Dirichlet model.

There is no evidence to suggest that private labels generally, attract more sole buying loyalty than any brand or than is predicted from theory. We examine loyalty to specific store's private labels in section 7.4.

We now examine duplicate buying.

7.3d Incidence And Rate Of Duplicate Buying Across Two Product Fields

Patterns of duplicate buying were discussed in detail in chapter 4 (section 4.2d page 118). On average some 16% of buyers remain completely loyal to the average group in 48 weeks (Table 7.3) which means the remainder have a repertoire of purchases, and switch between brands and private labels in both product fields.

Duplicate buying analyses across two product fields enables us to examine the issue of general private label proneness in more detail than in chapters 4 and 6. In this section we can determine whether those who buy private labels in one product field are more or less inclined to buy them in another.

We find that the way in which people spread their purchases across items in two product fields is much in line with the theory (Table 7.4). Both brand and private label groups share similar patterns of duplicate buying. Average

duplication falls in line with penetration (Table 7.1); in London average duplication falls from 62% to 35% and in Lancashire from 71% to 25%. This means that larger groupings attract more duplicate buyers than do smaller ones.

We might expect there to be more duplicate buying between private labels in both product fields, an indication of general private label proneness. However, there is only slight evidence of this. For example, in London, 36% of Squash private label buyers also buy Fabric Conditioner private labels as compared to (34%) predicted; 63% of Fabric Conditioner private label buyers also bought Squash private labels as compared to (60%) predicted. Similar results occur in Lancashire. The opposite is found for brand duplication. For example, 59% of Fabric Conditioner brand buyers also bought Squash brands, as compared to (62%) predicted. These differences are small, but nevertheless consistent. So there is some slight evidence that people who buy any private label in one product field are more inclined to buy them in another, a slight indication of general private label proneness.

Duplication coefficients are lower than found in chapters 4 and 6. This is because there are only four categories among which to switch. Also there is less switching between all stores brands and private labels in two product fields than, for example, within a product field in a store chain.

Table 7.4 : Incidence Of Duplicate Buying For Any Brand And Private Label Across Two Product Fields (48 weeks)

London					Lancashire				
Item	Sb	Spl	Fb	Fpl	Item	Sb	Fb	Spl	Fpl
Squash brd	*	66	53	32	Squash brd	*	53	52	20
Squash pl	68	*	46	36	Fab brd	65	*	36	29
Fab brd	59	50	*	38	Squash pl	84	74	*	24
Fab pl	57	63	62	*	Fab pl	63	74	47	*
Average	62	60	53	35		71	58	45	25
Pred	62	60	55	34		73	59	45	23

D = 1.12

D = 1.02

7.3e Summary

These analyses show how people buy any brand and any private label across two product fields. We find that when items are categorised in this way, patterns of purchase behaviour can on the whole still be described by the Dirichlet model. Though sole buying patterns are poorly predicted this was also found in chapter 6 (Tables 6.12 and 6.13) and so is not the result of purchasing being across two product fields.

Therefore, people buy items across two product fields in a similar way to buying in one. This is so for both brands and private labels.

It may seem surprising that even across two quite different product fields buyer behaviour patterns are similar. However, both are fast moving consumer goods which are regularly bought as part of the grocery basket. Regular patterns of buyer behaviour have been found to occur in a variety of individual product fields, so there is good reason why they should exist when the two product fields are merged.

In the within-store analyses, we showed that individual store's private labels attracted slightly more sole buying loyalty than the average brand and than is predicted from theory. This result is not evident in purchasing across two product fields. Sole buying patterns are similar for both groups which suggests that people are more loyal to individual store's private labels rather than to private labels generally. (We examine this further in section 7.4.)

Combining purchase behaviour across two product fields in this manner enables us to examine general private label proneness. One might expect that people who buy private labels in one product field to be more inclined to buy them in another. We find there is some slight evidence to support this in the two product fields examined. Furthermore, that those who buy brands in one product field are less inclined to buy them in another. These differences are small but consistent.

We now develop these results further by examining how people buy individual items across both product fields. Each brand and private label in each product field becomes one of a larger merged product field. The same analyses as shown above are followed, with much emphasis on specific private label proneness.

7.4 HOW PEOPLE BUY INDIVIDUAL ITEMS ACROSS TWO PRODUCT FIELDS

In this section, we examine how individual brands and private labels are bought across two product fields in the London region. In the previous section we found that people bought private labels generally in much the same way as brands. This section enables us to concentrate on specific store's private labels. For example, if there is any evidence to suggest that having bought a certain store's private label in one product field, the buyer is then more inclined to buy the same store's private label in another product field, this would indicate some specific private label proneness.

However, we need to take into account population at risk differences before we draw any interpretations from our results. First analyses without adjusting for population at risk are shown because the deviations found in chapter 4 also exist in purchasing across two product fields. Then we show results for within Sainsbury and Tesco store chains where the population at risk is the same for both brands and private labels being equivalent to the store's clientele. The fact the same deviation occurs prior to any population at risk adjustment being made and then is overcome thereafter, provides further empirical support to our population at risk explanation.

To differentiate between private labels in both product fields, "Sainsbury Sq" and "Sains fab" etc are used throughout. We follow the same analysis procedure as in section 7.3. First we examine penetration and purchase frequency; then the share of requirements ratio; and finally how people spread their purchases across both product fields. In order to avoid problems of small sample sizes, private labels with sample sizes of below 10 buyers or 1% market share are not shown.

7.4a Penetration And Average Purchase Frequency Across Two Product Fields

The high private label purchase frequency shows through in these analyses as it did in chapter 4 because no adjustment has been made for their mis-specified populations at risk (Table 7.5). Therefore, the Double Jeopardy pattern is evident only when brands and private labels are separated into two groups.

On average the model predictions are close; 20% (19%) of people buy brands and private labels and do so 3.9 (4.1) times. The difference in the values of

the components of the sales equation between brands and private labels is again evident. Private labels are bought by fewer people, more frequently than the average brand and than is predicted from theory; 21% (19%) of buyers buy brands and do so 3.4 (4.0) times as compared to 18% (20%) buying private labels 4.7 (4.1) times. This means that private labels are bought across both product fields in much the same way as they are in one.

Table 7.5 : Penetration And Average Purchase Frequency For Individual Items Across Two Product Fields (London 48 weeks)

Item	Market Share	b		w	
		O	T	O	T
Comfort	13	35	(33)	4.2	(4.5)
Sainsbury sq	17	30	(41)	6.6	(4.8)
OBsq	9	30	(24)	3.3	(4.2)
OBPLsq	10	30	(27)	3.9	(4.3)
Robinsons	9	28	(26)	3.8	(4.2)
Lenor	9	25	(25)	4.2	(4.2)
Quosh	6	20	(19)	3.7	(4.0)
Sainsbury fc	5	15	(16)	4.1	(3.9)
Kia-Ora	4	15	(11)	2.8	(3.8)
Tesco sq	5	11	(15)	5.4	(3.9)
OBPL fc	3	11	(8)	2.8	(3.8)
OB fc	1	9	(5)	2.0	(3.6)
Coop sq	4	8	(11)	5.2	(3.8)
Softlan	2	7	(5)	2.9	(3.7)
Overall Average		20	(19)	3.9	(4.1)
Average brand		21	(19)	3.4	(4.0)
Average private label		18	(20)	4.7	(4.1)

Note : average 24 week base used in fitting the Dirichlet model.

When analyses are undertaken at the within-store level so that the population at risk is more correctly specified, we find that the number of people buying and the rate at which they buy is much in line with the theory (Table 7.6). Though the Sainsbury and Tesco Fruit Squash private labels still have a high purchase rate, this does not generalise to the other Sainsbury and Tesco private labels where the w is lower than predicted. In Sainsbury, private label

Fruit Squash is bought by 30% (34%) of buyers 6.6 (5.8) times; Tesco private label Squash is bought by 11% (14%) of buyers 5.5 (4.3) times.

Table 7.6 : Penetration And Average Purchase Frequency Within Store Chains For Individual Items Across Two Product Fields (London 48 weeks)

	b		w			b		w	
	O	T	O	T		O	T	O	T
Sainsbury :					Tesco :				
Sainsbury FS	30	(34)	6.6	(5.8)	Tesco FS	11	(14)	5.5	(4.3)
Sainsbury FC	16	(15)	3.9	(4.1)	Comfort	8	(7)	3.2	(3.4)
Comfort	15	(13)	3.4	(4.0)	Lenor	7	(6)	2.6	(3.3)
Lenor	11	(9)	3.1	(3.8)	Robinsons	7	(6)	2.8	(3.3)
Robinsons	10	(11)	4.0	(3.9)	Quosh	7	(7)	3.4	(3.3)
OB FS	5	(3)	2.3	(3.5)	Tesco FC	6	(4)	2.2	(3.1)
RB	4	(3)	3.4	(3.5)	OB FS	2	(1)	2.1	(2.9)
Kia Ora	3	(3)	3.5	(3.5)	RB	2	(1)	2.8	(2.9)
Softlan	2	(1)	1.9	(3.4)	Sosoft	1	(1)	1.8	(2.9)
Sosoft	1	(1)	1.4	(3.4)					
Quosh	1	(1)	1.1	(3.4)					
Average	9	(9)	3.2	(3.9)	Average	6	(5)	2.9	(3.3)

Note : average 24 week base used in fitting the Dirichlet model; FS - Fruit Squash, FC - Fabric Conditioner.

Overall, this means that once the population at risk adjustment is made, the private label w is no longer consistently high even when examining purchase behaviour across two product fields. Again it is important to stress that the private label purchase rate is likely to be high on some occasions and low on others. However, once the population at risk adjustment is made, the consistent deviation is overcome.

We now consider how buyers of both product fields distribute their purchases across the items available.

7.4b Product Purchase Rate And Share Of Requirements Ratio Across Two Product Fields

We find that rates of buying both product fields vary little from 17 to 22 times in 48 weeks and are closely predicted by the model (Table 7.7). This is

similar to what was found in chapters 4 and 6. On average buyers make 19 purchases of Fruit Squash and Fabric Conditioner as compared to the (18) predicted. The share of requirements ratio is more variable and not in line with predictions. But this is mainly due to the variation in purchase frequencies between brands and private labels resulting from the population at risk problem.

Table 7.7: Product Purchase Rates And Share Of Requirements Ratio For Individual Items Across Two Product Fields (London 48 weeks)

Item	wp		w/wp	
	O	T	O	T
Comfort	17	(17)	25	(26)
Sains Sq	18	(17)	36	(28)
OB Sq	20	(18)	17	(24)
OBPL Sq	19	(17)	21	(24)
Robinsons	20	(17)	19	(24)
Lenor	17	(18)	25	(24)
Quosh	21	(18)	17	(22)
Sains Fc	18	(18)	22	(22)
Kia-Ora	22	(18)	13	(21)
Tesco Sq	22	(18)	24	(22)
OBPL Fc	20	(18)	14	(20)
OB Fc	20	(18)	10	(20)
Coop Sq	22	(18)	24	(21)
Softlan	21	(18)	14	(20)
Overall Average	19	(18)	20	(23)
Average brand	20	(18)	18	(23)
Average pl	20	(18)	24	(23)

Note : average 24 week base used in fitting the Dirichlet model.

When we examine product field buying within the store, we find that brands and private labels are bought in much the same way and largely in line with the theory (Table 7.8). For example, people make 11 (11) Sainsbury private label Squash purchases, and this accounts for nearly 60% of its buyers needs. There are some deviations but these result from the low purchase rates of small brands in both stores.

Table 7.8 : Product Purchase Rates And Share Of Requirements Ratio Within Store Chains For Individual Items Across Two product Fields (London 48 weeks)

	wp		w/wp		w		w/wp		
	O	T	O	T	O	T	O	T	
Sainsbury :					Tesco :				
Sainsbury FS	11	(11)	57	(54)	Tesco FS	10	(9)	23	(27)
Sainsbury FC	12	(13)	34	(32)	Comfort	9	(11)	36	(31)
Comfort	10	(13)	34	(30)	Lenor	9	(11)	30	(29)
Lenor	13	(14)	25	(28)	Robinsons	11	(11)	25	(29)
Robinsons	14	(13)	28	(29)	Quosh	12	(11)	28	(31)
OB FS	16	(14)	14	(25)	Tesco FC	9	(11)	53	(46)
RB	13	(14)	27	(25)	OB FS	15	(12)	14	(24)
Kia-Ora	17	(14)	20	(25)	RB	20	(12)	14	(24)
Softlan	17	(14)	11	(24)	Sosoft	18	(12)	10	(24)
Sosoft	16	(14)	9	(24)					
Quosh	9	(14)	12	(24)					
Average	14	(13)	25	(29)	Average	13	(11)	26	(30)

Note : average 24 week base used in fitting the Dirichlet model.

Therefore, there is no evidence of any heightened loyalty to private labels in this respect over and above what is expected from their market share levels. The Dirichlet model provides a good estimate for product field purchasing across two product fields.

7.4c Incidence And Rate Of Sole Buying Across Two Product Fields

When the two product fields are merged, patterns of sole buying do not follow the same patterns as described in chapter 4 (section 4.2d page 112). The model fit for sole buying patterns generally has been variable, and is particularly poor here.

The incidence of sole buying varies unsystematically between the different items, rather than those with larger market shares attracting more sole buying loyalty (Table 7.9). Though on average the overall fit of the model is fairly close; 7% (5%) of buyers are sole buyers who make 3.0 (2.4) purchases in 48 weeks, there is much variation at the individual item level. However, this variation occurs for both brands and private labels so does not affect the main

comparison. For example, 13% (7%) of buyers are loyal to Sainsbury private label Fruit Squash and they make 6.9 (3.0) purchases in 48 weeks.

Table 7.9 : Incidence And Rate Of Sole Buying For Individual Items Across Two Product Fields (London 48 weeks)

Item	bs		ws	
	O	T	O	T
Comfort	14	(6)	2.7	(2.7)
Sains Sq	13	(7)	6.9	(3.0)
OB Sq	8	(5)	1.7	(2.5)
OBPL Sq	8	(6)	3.3	(2.6)
Robinsons	5	(6)	1.4	(2.6)
Lenor	7	(5)	7.6	(2.5)
Quosh	7	(5)	5.4	(2.4)
Sains FC	8	(5)	3.3	(2.4)
Kia-Ora	2	(5)	2.0	(2.3)
Tesco Sq	6	(5)	2.3	(2.4)
OBPL FC	10	(5)	2.6	(2.3)
OB FC	0	(4)	0	(2.2)
Coop Sq	2	(5)	3.0	(2.3)
Softlan	2	(4)	1.0	(2.2)
Overall Average	7	(5)	3.0	(2.4)
Average brand	8	(5)	3.0	(2.4)
Average pl	7	(5)	3.0	(2.4)

Note : average 24 week base used in fitting the Dirichlet model.

The detailed fit of the model is still poor for analyses at the within-store level (Table 7.10). We find that on the whole larger items (both brands and private labels) attract slightly more sole buying loyalty than the model predictions, and smaller items attract less. For example, 34% (32%) of buyers are sole Sainsbury Squash buyers and they make 5.1 (3.8) purchases; whereas 5% (13%) are Kia-Ora sole buyers making 1.0 (2.0) purchases in 48 weeks.

Table 7.10 : Incidence And Rate Of Sole Buying Within Store Chains For Individual Items Across Two Product Fields (London 48 weeks)

	O	bs T	O	ws T		O	bs T	O	ws T
Sainsbury :					Tesco :				
Sainsbury FS	34	(32)	5.1	(3.8)	Tesco FS	30	(17)	1.4	(1.7)
Sainsbury FC	20	(17)	2.9	(2.4)	Comfort	35	(19)	1.8	(1.9)
Comfort	25	(16)	2.6	(2.3)	Lenor	32	(18)	2.2	(1.8)
Lenor	20	(15)	3.4	(2.2)	Robinsons	18	(18)	1.5	(1.8)
Robinsons	8	(15)	2.0	(2.2)	Quosh	30	(19)	2.9	(1.8)
OB FS	6	(13)	1.0	(2.0)	Tesco FC	32	(29)	1.8	(2.5)
RB	17	(13)	1.0	(2.0)	OB FS	7	(15)	1.0	(1.6)
Kia-Ora	5	(13)	1.0	(2.0)	RB	0	(15)	0	(1.6)
Softlan	0	(13)	0	(2.0)	Sosoft	11	(15)	1.0	(1.6)
Sosoft	0	(13)	0	(2.0)					
Quosh	11	(13)	1.0	(2.0)					
Average	13	(16)	1.8	(2.3)	Average	22	(19)	1.5	(1.8)

Note : average 24 week base used in fitting the Dirichlet model.

In chapter 4, we found that private labels had a higher rate of sole buying than brands and than the model predictions. When analyses were undertaken at the within-store level in chapter 6, there were still signs that private labels attracted slightly more sole buying loyalty and this was reflected in both the number of sole buyers and their rate of buying. However, the above analyses suggest that it is not private labels generally which attract more sole buying loyalty, but items with larger market shares.

This point did not show through in chapter 6 results (Table 6.13 page 206) because the average brand included many smaller brands which pulled down the average in comparison to that for private labels which tend to have high market shares. However, these results are far from conclusive; three brand leaders were examined in chapter 6 (Table 6.14) and these did not attract more sole buying loyalty despite having high market shares. More work is needed to explore sole buying and substantiate these results.

Overall though the evidence suggests that brands and private labels attract similar levels of sole buying loyalty. Because private labels tend to achieve high market shares, they attract slightly more sole buying loyalty than the average brand and than is predicted from theory. Whether they achieve more than any other brand leader cannot be answered from these limited analyses.

7.4d Incidence And Rate Of Duplicate Buying Across Two Product Fields

Duplication patterns were discussed in chapter 4 (section 4.2d page 117). In Table 7.9 it was shown that on average only 7% of its buyers remained loyal to one item in 48 weeks. The majority of buyers therefore switch between different items for their purchases in both product fields.

Regular patterns of duplicate buying are found when both product fields are combined. Average duplication falls roughly in line with penetration; from 47% to 11% (Table 7.11). Predicted duplication is close to the observed level, with the maximum deviation being 8 points for the Sainsbury Fruit Squash private label. Duplication figures are of a similar order of magnitude within each column, though some systematic discrepancies exist which are discussed below.

This means that on the whole items attract the level of duplicate buying that their market shares warrant; larger items attract more duplicate buyers than smaller ones; and duplicate buying patterns are similar to those found in one product field (Table 4.21 page 120).

Table 7.11 : Incidence Of Duplicate Buying For Individual Items Across Two Product Fields (London 48 weeks)

Item	Co B FC	Sa PL S	OB B S	OB PL S	Ro B S	Le B FC	Qu B S	Sa PL FC	Ki B S	Te PL S	OB PL FC	OB B FC	Co PL S	So B FC
Comfort	*	29	35	28	33	41	24	21	19	12	15	15	11	13
Sains Sq	34	*	43	43	43	22	24	30	19	13	13	8	7	9
OB Sq	41	43	*	44	46	27	35	18	28	17	14	12	12	10
OBPL Sq	34	44	45	*	41	20	28	19	23	19	18	12	11	7
Robinsons	41	22	49	43	*	26	35	46	31	19	15	12	11	9
Lenor	58	28	34	24	31	*	24	21	18	14	15	17	11	13
Quosh	42	36	52	42	49	30	*	15	31	22	15	12	17	7
Sains FC	45	58	35	36	38	33	18	*	16	11	21	12	6	13
Kia-Ora	43	37	58	45	58	29	40	17	*	16	19	15	15	11
Tesco Sq	39	36	47	51	49	31	40	17	22	*	17	14	14	7
OBPL FC	51	36	41	51	39	35	29	32	28	17	*	20	13	17
OB FC	60	26	41	41	38	47	28	21	26	17	24	*	17	17
Coop Sq	51	27	47	41	39	33	43	12	29	20	18	20	*	10
Softlan	67	38	42	31	36	47	20	29	24	11	27	22	11	*
Average	47	35	44	40	42	32	30	23	24	16	18	15	12	11
Predicted	50	43	43	42	40	35	28	23	22	16	15	13	11	10
Deviation	-3	-8	1	-2	2	-3	2	0	2	0	3	2	1	1

D = 1.39

Note : Abbreviation in row 1 refer to items listed down the side of the table.

B - brands, PL - private labels, FC - fabric conditioner,
FS - fruit Squash.

However, there are some interesting discrepancies in Table 7.11 which relate to specific private label proneness. The relevant information is summarised in Table 7.12. The incidence of duplication between the same store's private labels (bold figures) is on average 150% higher than predicted. This means that people who buy the Sainsbury private label in one product field, are much more likely to then buy it in another. For example, duplication between Sainsbury private label Fabric Conditioner and Squash is 58%, compared to (43%) predicted; in Tesco the figures are 42% (16%), and for Coop, 52% (11%). The same high duplication occurs between Squash buyers who also buy Fabric Conditioners. In contrast duplication between different store's private labels is on average 25% below the predicted level.

**Table 7.12 : Incidence Of Duplicate Buying Between Private Labels
Across Two product Fields (London 48 weeks)**

Item	Fruit Squash			Fabric Conditioner		
	Sain	Tesc	Coop	Sain	Tesc	Coop
Fruit Squash						
Sain	*	13	7	(30)	6	4
Tesco	36	*	14	17	(24)	6
Coop	27	20	*	12	6	(24)
Fabric Conditioner						
Sains	(58)	12	6	*	11	3
Tesco	27	(42)	7	27	*	5
Coop	30	17	(52)	3	9	*
Average*	35	18	14	21	10	7
Predicted	43	16	11	23	9	7

Note* : averages are for all items in Table 7.11; Tesco and Coop Fabric Conditioners were not shown in Table 7.11 because of small sample sizes, however they are shown above in a limited form.

It has not been possible to replicate these analyses for the Lancashire region because of operational problems. However, the biscuit market (Note 3) has also been examined where the store's private label is available in more than one variety. Though this differs somewhat from purchasing across two product fields, the principle of proneness to specific private labels is the same.

We find there is high duplication between the same store's private label varieties (Table 7.13). Sainsbury and Tesco duplication are summarised below, with the full table of 24 items is shown in Appendix 13. The average duplication with the same store's private label varieties are consistently higher than predicted, as seen in the last two rows of Table 7.13. For example, Sainsbury private label digestives are also bought by an average of 56% of buyers of other Sainsbury private label varieties as compared to (18%) predicted. The same occurs for duplication with Tesco varieties.

Note 3 : Tabulated data for the UK biscuit market was provided as part of a consultancy project undertaken on behalf of United Biscuits.

**Table 7.13 : Incidence Of Private Label Duplicate Buying For Biscuits
(London 48 weeks)**

Sainsbury Varieties					Tesco Varieties	
Item	Dig	Choc	Fing	Shrt	Item	Dig Whole
Digestive	*	46	48	45	Digestive	* 40
Choc. Dig	52	*	43	44	Wholemeal	41 *
Fingers	59	46	*	49		
Shortcake	57	49	50	*		
Average	56	47	50	46	Average	41 40
Predicted	18	16	14	14	Predicted	11 11

Note: the averages are from items shown above; predicted figures are from the full table shown in Appendix 13 where D=1.6.

The incidence of duplication between the same store's private label varieties is on average 240% higher than predicted. Duplication between these and other private labels or brands is on the whole lower than predicted. By comparison, there is no evidence of high duplication between varieties of the same brand. For example, there are seven McVitie brands available in the biscuit market and duplication between them is much as predicted (Table 7.14).

Table 7.14 : Incidence Of Duplicate Buying Between McVitie Varieties (London 48 weeks)

Item	Dig	Rich	Wh	Hob	Jaf	Gin	Frt
Digestive	*	50	43	38	28	30	20
Rich Tea	62	*	39	37	29	34	21
Wholeweat	59	43	*	40	34	31	23
Hob Nob	58	45	44	*	29	32	24
Jaffa	53	45	48	37	*	30	23
Ginger	59	54	44	41	31	*	27
Fruit	59	50	49	46	34	40	*
Average	58	48	45	40	31	33	23
Predicted	62	50	45	42	32	32	21
Deviation	-4	-2	0	2	-1	1	2

Note : the averages are from items in Table 7.14; predicted figures are from the full table shown in Appendix 13.

Unfortunately no other data is available to enable us to generalise the McVitie result further. However, McVitie is a leading brand name in the biscuit market and as a result one might expect any "brand umbrella effect" to show through here.

These results suggest that people are prone towards buying specific store's private labels, be this across 2 product fields or for different varieties within the same product field. So specific private labels tend to benefit from some kind of umbrella effect which does not exist for brand names such as McVities.

However, these analyses do not take into account the relevant population at risk. So low duplication between different store's private labels and high duplication between private labels in the same store may simply be a store effect. This means it is a reflection of the lack of opportunity to buy the private labels of other stores rather than any conscious private label proneness.

It has been shown that people switch between different stores for their purchases, even within the same product field (Ellis and Uncles 1989 Appendix 12, Kau 1981, Lamb and Goodhardt 1989). So the opportunity to duplicate with other stores' private labels is not as low as may seem initially. Nevertheless, the ability to duplicate with other private labels is lessened as a result.

To determine whether this is a store effect or some real specific private label proneness, duplication across two product fields within the store chain is examined. In fact we find that duplication is lower than predicted between the two Sainsbury private labels (Table 7.15); 58% of Sainsbury Fabric Conditioner buyers also buy Sainsbury Fruit Squash as compared to 75% predicted; 30% of Sainsbury Fruit Squash buyers also buy Sainsbury Fabric Conditioner as compared to 39% predicted. The same results occurs for the two Tesco private labels.

Table 7.15 : Incidence Of Duplicate Buying For Individual Items Within Store Chains Across Two Product Fields (London 48 weeks)

Sainsbury :

	Sa FS	Sa FC	Co FC	Le FC	Ro FS	OB FS	RB FS	Ki FS	So FC	Ss FC	Qu FS
Sainsbury FS *		30	23	17	26	13	8	6	5	3	4
Sains FC	58	*	29	27	22	12	8	5	7	6	4
Comfort	47	31	*	33	19	8	8	4	7	1	2
Lenor	49	40	46	*	16	17	7	6	4	3	4
Robinsons	77	35	27	17	*	23	18	8	6	4	3
OB	76	36	24	36	45	*	27	12	3	9	12
RB	52	35	35	22	22	17	*	13	9	0	0
Kia-Ora	73	23	18	18	55	41	14	*	9	5	0
Softlan	60	47	47	20	27	7	13	13	*	7	0
SoSoft	71	86	14	29	43	43	14	0	14	*	0
Quosh	89	44	22	33	22	44	0	0	0	0	*
Average	65	41	29	25	30	22	8	11	6	4	3
Predicted	75	39	36	27	25	13	9	8	6	3	3

D = 2.46

Tesco:

	Te FS	Co FC	Le FC	Ro FS	Qu FS	Te FC	OB FS	RB FS	So FC
Tesco FS	*	21	18	35	28	24	15	8	8
Comfort	31	*	37	22	20	20	10	6	8
Lenor	28	38	*	28	26	26	11	6	9
Robinsons	56	24	29	*	38	22	22	16	4
Quosh	47	23	28	40	*	23	21	14	5
Tesco FC	43	25	30	25	25	*	15	8	5
OB FS	73	33	33	67	60	40	*	13	0
RB	60	30	30	70	60	30	20	*	10
SoSoft	67	44	44	22	22	22	0	11	*
Average	50	30	31	39	35	26	14	10	6
Predicted	53	36	34	33	31	29	11	7	7

D = 4.76

This means that once the correct population at risk is defined, people buy brands and specific store's private labels interchangeably and largely in line with their market shares. There is no evidence from these limited analyses to suggest that having bought a particular store's private label in one product field, a person is then more inclined to then buy it in another. Indeed, the opposite seems to occur slightly.

Furthermore, this is also true for the brand leaders in each product field. In Tesco for example, 24% of Robinsons buyers also buy Comfort as compared to (36%) predicted; 22% of Comfort buyers also buy Robinsons as compared to (33%) predicted. The same occurs in Sainsbury stores.

7.4e Summary

Buying patterns for individual items across two product fields show similar deviations to chapter 4 results. This is particularly noticeable with the high purchase rate and high duplication between the same store's private label. However, once the analyses are confined to within-store chains, we find that brands and private labels are bought much in line with the theory. Private labels attract a similar number of buyers, who make a similar number of purchases as brands. Product purchase rates and share of requirement ratios are also much the same.

There is much unsystematic variation in sole buying patterns and model predictions are poor. This occurs for both brands and private labels so does not affect the main comparison. Items with larger market shares seem to attract more sole buyers who make slightly more purchases than predicted. The opposite occurs for items with smaller market shares. In these analyses there is no consistent evidence that private labels attract more sole buying loyalty than any other brand leader. Only that larger items generally do.

Though initially, it seemed that people were prone to buy specific store's private labels, once we examine duplicate purchasing within-store chains, we find this is a store effect. Indeed, from these limited analyses it seems that people are slightly less inclined to buy a specific store's private label in one product field when they have bought it in another. Furthermore, this is also true for duplication between brand leaders in each product field.

7.5 SUMMARY AND CONCLUSIONS

We have shown that the Dirichlet model can also be used to estimate purchasing across two product fields, whereas previously it has only been tested in one at a time. This is so for both brands and private labels. However, the fit of the model is not as good as is usually found when applied to purchasing in one product field, and there is much unsystematic variability for individual item sole buying patterns in particular. Sole buying was also poorly predicted in chapter 6 which seems to be a general problem with the model.

It may seem surprising that people buy across two product fields in a similar way as they buy in one, especially given the different nature of the two product fields studied. However, both are frequently bought and available in a variety of stores where the consumer has to make a relatively low-involvement purchase decision. So the fundamentals of buying in any fast moving consumer good product field are similar, and this seems to be reflected in peoples' purchasing patterns. Furthermore, the model specifies independence between purchases of items within the same product field, and this is perhaps more intuitively obvious for purchases across two product fields. On average, items in the two product fields are bought as though they were no different in anything other than their market shares.

The population at risk effects show through in the analysis of individual items. Private labels have a high purchase rate, a higher share of requirements ratio, and the store effect is most noticeable in the duplication analyses. So even across two product fields, the same type of deviations as in chapter 4 are found. When analyses are confined to within store chains, the systematic differences no longer exist. This adds further support to our population at risk explanation.

Indeed, we find that private labels are bought in two product fields in much the same way as are brands, once market share differences have been allowed for.

There is no strong evidence to suggest that private labels attract more sole buying loyalty from their buyers than brands, even within the same store. Though in chapters 4 and 6 we found signs that private labels attracted more sole buying loyalty, the evidence suggests this is more of a large item effect that anything to do with private labels per se. Because private labels tend to achieve such high market share levels, they attract more sole buying loyalty than predicted. However, whether this is more than for any other large brand cannot

be answered from these limited analyses because results are inconclusive. Further work is needed to substantiate these results.

People buy the same store's private labels interchangeably, and do so much in line with their market share levels. However, there were some signs that people were general private label prone, and this did not occur for the brand grouping. There has been much concern with private labels proneness (Cunningham 1961, Rao 1969a) which is discussed more in chapter 9. These results suggest that there is some slight evidence of proneness towards private labels generally, which does not exist for brands. But there are no signs of any specific private label proneness. Indeed, when analyses are confined to within store chains there is evidence to suggest that people who have bought a specific store's private label in one product field are less inclined to then buy it in another.

The analyses in this chapter are limited to only two product fields. Therefore, results should be seen as exploratory. Further work is needed before any firm conclusions should be drawn, but these early results are encouraging for further research.

DISCUSSION

CHAPTER 8 - TESTING THE MODEL ASSUMPTIONS AND LIMITATIONS OF THIS STUDY

CHAPTER 9 - CONCLUSIONS AND DISCUSSION

CHAPTER 8 : TESTING THE MODEL ASSUMPTIONS AND THE LIMITATIONS OF THIS STUDY

8.1 Introduction**8.2 Model Assumptions****8.2a Stationarity****8.2b Market Segmentation****8.3 Data Used****8.4 Operational Limitations****8.5 Further Work****8.6 Summary**

8.1 INTRODUCTION

As with any research, there are limitations which need to be appreciated in interpreting the results. These relate particularly to the model assumptions, the data used and operational limitations. We examine each in turn.

8.2 MODEL ASSUMPTIONS

Models are invariably a simplified representation of some parts of the real world. Their representativeness and validity generally depend on the assumptions made, and on other constraints imposed by the environment.

The NBD and Dirichlet assumption of stationarity, for example, means that neither model are capable of predicting buying behaviour in a dynamic situation. The models do not aim to predict what will happen if the stationarity of the market is disturbed. They can predict buyer behaviour in one stationary state and then in another, but not in the change period between. Once a new stationary state is reached, their use can be resumed.

This is in fact less restrictive than has often been believed because markets are basically stationary most of the time, especially in the short or medium term. Analyses using these models have been limited to time periods of at most one year, where markets are more or less stationary anyway. For example, a disturbance such as that arising from the introduction of a private label would produce only a temporary disequilibrium. A return to a new stationary state would be expected within a short time period. In such cases the models can be used to supply theoretical norms against which the effects (or otherwise) of temporary non-stationary conditions can be gauged.

Model predictions have been used as theoretical norms against which the observed data are compared throughout the thesis. Therefore, the predictions form the lynchpin of the analyses and subsequent interpretation. As such, there is an implicit assumption that the model assumptions have largely been fulfilled in practice so that it is feasible to use the predictions in this way. We show that on the whole the assumptions are fulfilled so that predictions based on these assumptions are not refuted. Even when this is not so, the models can still be used, albeit in a more diagnostic manner.

Though, the model assumptions have already been discussed in some detail in

previous chapters (section 3.4a, 3.5a, 5.5), they are summarised again here: The NBD model assumes the items sales are stationary over time; the Dirichlet that the market is both stationary and unsegmented. We examine each assumption in turn.

8.2a Stationarity

Consumer behaviour is considered to be stationary when the aggregate level of purchasing remains approximately equal from one time period to the next. This has been found to be approximately so in the lengths of time period analysed for most fast moving consumer goods studied in the thesis and more widely (Ehrenberg 1972, 1988).

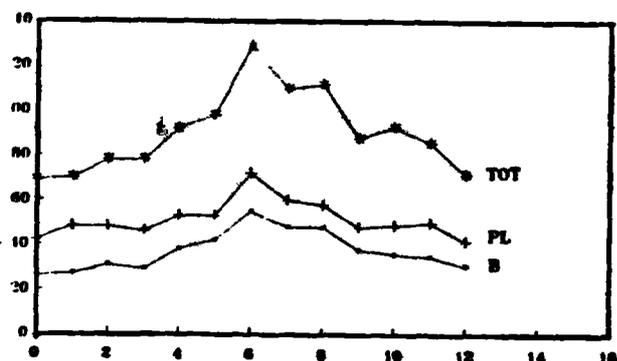
It is important that the assumptions are either fulfilled in practice or at least to be aware when they are not so that this can be taken into account in interpreting results. For example, if the product fields examined are not stationary or just private labels, non-stationary, this would result in deviations from the theoretical predictions.

In this section we show that in reality our data is not completely stationary, but even in the two seasonal product fields, the models can still be used because brands and private labels have similar degrees of non-stationarity (Graphs 8.1 to 8.10).

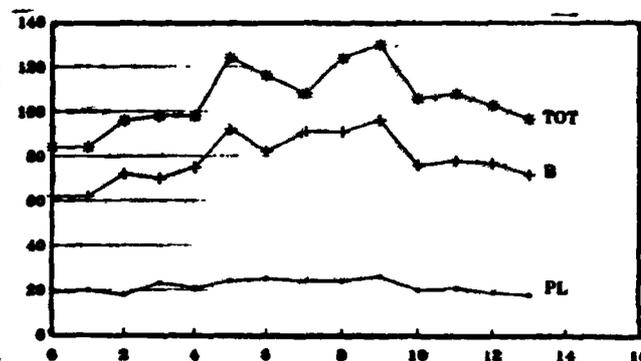
Graphs 8.1 to 8.10 : Sales (b*w) For Average Brand And Private Label In Five Product Fields (48 weeks)

Fruit Squash :

Graph 8.1 : London

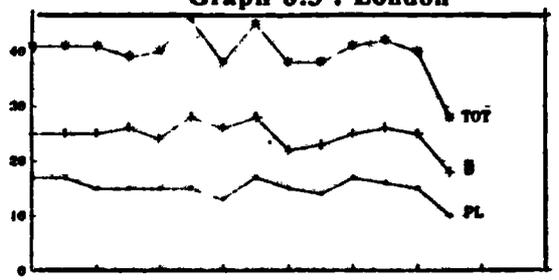


Graph 8.2 : Lancashire



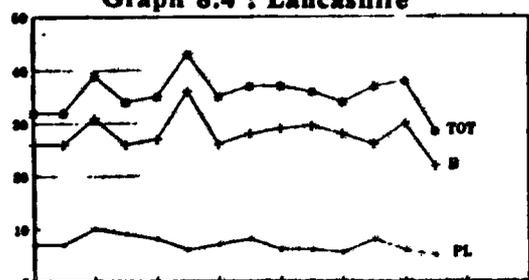
Fabric Conditioner :

Graph 8.3 : London

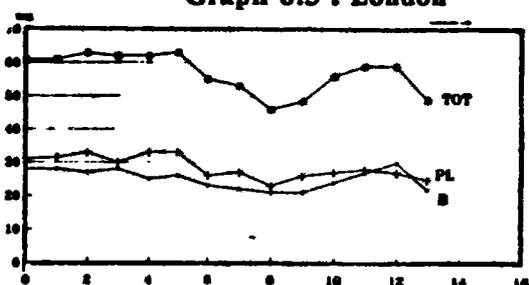


Baked Beans :

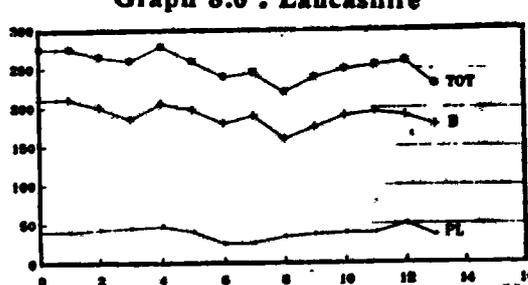
Graph 8.4 : Lancashire



Graph 8.5 : London

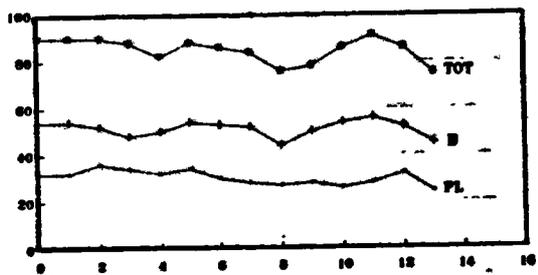


Graph 8.6 : Lancashire

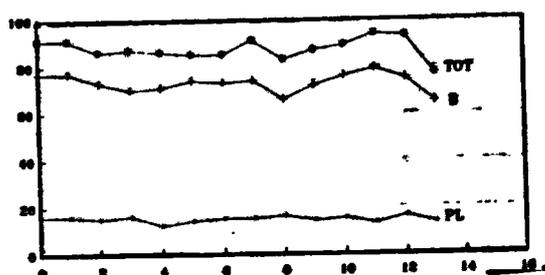


Instant Coffee :

Graph 8.7 : London

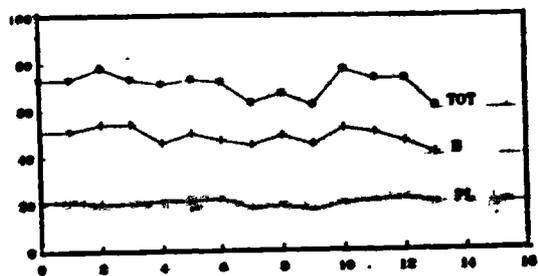


Graph 8.8 : Lancashire

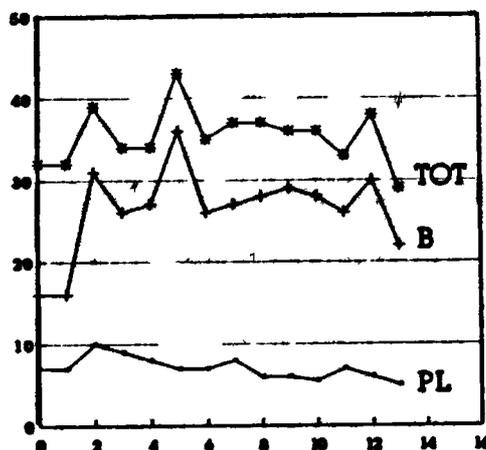


Washing Up Liquid :

Graph 8.9 : London



Graph 8.10 : Lancashire



In an ideal world, the data would be completely stationary and, as long as the other assumptions were satisfied, the models would describe the data exactly. However, in reality, markets are not quite stationary because of new product launches, seasonality and general marketing effects. There are two main types of non-stationarity in the data; irregular movements around a steady base line and seasonality.

The former do not usually produce major deviations from the theoretical predictions. Though sales fluctuate over time as marketing activities are undertaken, data are aggregated into sufficiently long time periods to try and smooth out short-term fluctuations and minimise deviations from the model. However, sole and repeat buying patterns were deviant but the former seems to be a general problem with the model and the latter due to small sample sizes. More minor deviations in such as the purchase frequency distribution are more likely to be a result of non-stationarity.

Though only limited research has been undertaken on seasonality, it was found that on the whole the models still describe buying patterns. The main finding from one study was that the sales increase during the peak season was a result of more new buyers, rather than existing buyers buying more often (Wellan 1985, Wellan and Ehrenberg 1988). Seasonality mainly affects period to period buying and other measures examined over time because of this influx of new buyers during the seasonal peak. So sales change from one time period to another which violates the stationarity assumption.

Fruit Squash and Baked Beans are seasonal product fields. Fruit Squash has a seasonal peak during the summer, and sales of Baked Beans fall in the same period. Despite this, the models are still used to provide norms against which to compare brands and private labels. This is because the seasonal peaks and troughs fall in the middle of the year, so sales in each of the two 24 week periods are similar. The average of these two 24 week periods is used as input to the model so theoretical buying patterns do not seem to differ from those in the non-seasonal product field because the 24 week base essentially smooths out the effects of seasonality. Therefore, whether the product field is stationary or seasonal, this does not inhibit using the models to provide theoretical norms.

Although our data is not completely stationary be it due to seasonality or

irregular movements, this does not prevent us from using the models as our norm. The focus of the thesis is a comparison between brands and private labels, so seasonality and other forms of non-stationarity do not directly interfere with this comparison except to make it more difficult. Non-stationarity causes problems if it varies for brands and private labels, or if non-stationarity affects them in a differential manner. If this was the case it would result in model deviations which differed for brands and private labels making it difficult to identify which differences were a result of private labels, and which were due to non-stationarity.

We have already shown that brand and private label sales ($B * W$) are similar in graphs 8.1 to 8.10. We now show that brands and private labels have similar degrees of non-stationarity by calculating standard deviations for each item's sales over the 48 week period, and then averaging these for brands and private labels in each product field. Though standard deviations measure variation about the mean and take no account of absolute differences in the sales of each product field, this does not matter because our comparison is for brands and private labels within the same product field. On average private labels are slightly more stationary than brands, with standard deviations of 1.2 and 1.7 respectively (Table 8.1). However, this is not a consistent finding and varies between product fields.

Table 8.1 : Standard Deviation For Sales (Penetration * Purchase Frequency) Of The Average Brand And Private Label For Five Product Fields (48 weeks)

Product Field	Region	brands	pls
Fruit Squash	London	1.7	1.3
	Lancashire	1.9	0.7
Fabric Conditioner	London	0.7	0.6
	Lancashire	1.6	0.8
Baked Beans	London	2.6	3.4
	Lancashire	3.8	1.2
Instant Coffee	London	0.8	1.2
	Lancashire	1.1	0.9
Washing Up Liquid	London	1.5	0.7
	Lancashire	1.1	0.8
Average		1.7	1.2

In order to determine whether seasonality affects brands and private labels differently, we use the models. The Dirichlet and NBD are fitted to 3 time periods. For example, Fruit Squash; pre peak season (weeks 1 to 16), peak season (weeks 17 to 32) and post peak season (weeks 33 to 48). We find that the Dirichlet model predicts purchase behaviour for brands and private labels similarly within each season. There are some discrepancies, but these occur for all items.

Therefore, in three of our product fields, brands and private labels have similar degrees of non-stationarity. In Fruit Squash and Baked Beans, the seasonal pattern is similar for all items. So the models can be used because non-stationarity does not directly interfere with our main comparison.

We now briefly examine the assumption of market segmentation.

8.2b Market Segmentation

On the whole, there are no consistent or sizeable signs of market segmentation in the five product fields studied. Segmentation can be based on the type of buyer, ie their socio-economic and demographic profiles, and on their buying behaviour, ie private label or brand buyers.

Segmentation has been examined in chapters 4 (section 4.2d page 117), 6 (section 6.3d page 209) and 7 (sections 7.3d and 7.4d pages 229 and 239). It might be thought that people engage in selective private label buying ie mainly buy Tesco private labels or private labels generally. However, our results show that people buy brands and private labels interchangeably, and much in line with the predicted levels. Indeed, on the whole they are bought as though the only difference is in their market share levels.

Furthermore, one might think that people who buy private labels are somehow different to those who buy brands. In chapter 5 (section 5.5 page 168), we found that private labels were bought by a similar social class and household size profile. Though these are the only two demographics shown, others were analysed including; ITV viewing status, age of housewife, presence of children and housewife working status. So private label buyers comprise the same types of people as brand buyers. There were no consistent demographic differences between brand and private label buyers.

Therefore, the model assumptions are largely satisfied and even when they are not, we find the models can still be used as norms because any deviations affect brands and private labels in much the same way.

8.3 DATA USED

The reliability and validity of the observed purchasing data could be questioned. At their simplest, the analyses could be regarded as dealing with certain reported purchasing claims treated at face value without necessarily implying the data need or must represent the populations real purchasing behaviour.

However, general experience from some specialised studies suggest that diary panel techniques are fairly free from any important bias when measuring consumer purchase behaviour (Sudman 1964a and 1984b, Ehrenberg 1960). There is evidence to show that cooperators and non-cooperators do not differ systematically in their purchasing behaviour. Also that the length of panel membership does not produce any changes in purchasing claims (Ehrenberg 1960, Ehrenberg and Twyman 1966). Furthermore, there are many different consumer behaviour panels and similar purchasing patterns are found to occur in each.

As with any data collection procedure there are problems such as errors in entering the information which increase as the product recording details become more complex; and differences in the recording accuracy of products depending on their position in the diary; and memory lapses where the purchaser forgets to record all purchases.

AGB panel data is used in the thesis where data is collected by means of an in-home audit rather than by a self completion diary. This overcomes some of the problems associated with self completion panels because a trained interviewer visits the panelist's home and records the household's purchases in the diary. This reduces input error and is particularly useful in collecting information on more complex product fields.

But other problems arise with such as households throwing away wrappings from perishable and snack items rather than keeping them for the interviewers visit. Pick up rates (the accuracy with which the panel measures the product field) and coverage (the accuracy with which the panel measures the item in question) may therefore differ by product field. Of the five product fields studied, none seem to be particularly vulnerable to these problems in any major way.

More recently scanner panel data, where household purchases are continuously monitored by using Universal Product Code scanners, have become more popular. These are now offered by companies like Information Resources Inc. (IRI) of America with their Behaviourscan panel. The panelist simply shows an identity card at the point of sale and her purchases are recorded electronically. Studies have found that scanner panel data is more accurate with the recording of small item purchases (Fulgoni 1982).

However, this does not invalidate the use of panel data. Indeed panel data has been shown to be more accurate than such as recall techniques (Sudman 1964b) where for example, leading brands have their shares overstated by as much as 50% and small brands are understated. In-home audit panel data does have problems associated with it, and these should be borne in mind in interpreting the results.

The choice of product fields limits the scope of the results to some extent. All five product fields are fast moving consumer goods product fields. It would have been interesting to compare private label purchasing patterns in product fields where branding is particularly strong. For example in the cosmetics and perfumery business, would private labels achieve the same levels of success as in the grocery market? These issues are discussed more in Chapter 9.

Only two product fields have been examined in detail using raw data, and another three from tabulated output. Those results based on two product fields in particular need to be generalised further to ensure their robustness. Though only a limited number of product fields have been examined, an attempt has been made to select data sets so that comparisons can be made across a range of characteristics. For example, high/low private label market shares, different regions, food/non-food, store chains with different private label policies and seasonal and non-seasonal product fields. Nevertheless, the generalisability of the results are limited and more work is needed.

There are some characteristics which have not been catered for. For example, comparing how people buy in a product field with no private labels with one that was completely private label. This has been overcome to some degree by comparing buying patterns in product fields in KwikSave, where no private labels exist, with those in Marks and Spencer, a 100% private label operation (Ellis and Uncles 1989 Appendix 12). It would have also been interesting to compare product fields where the purchaser buys for the family with those where the purchase is for a gift or

social occasion because private labels may be used more for private "consumption".

Furthermore, very little can be said of the components of store traffic as only five product fields are examined. These comprise only a fraction of the consumers total shopping basket. An attempt to see how people buy items across two product fields was made in chapter 7. This is a first step towards being able to identify how the store clientele distribute their purchases across the store's product range. For example, do a few product fields attract all shoppers, or are some bought by a few heavy buyers. Chapter 7 results are encouraging for further research.

Purchasing records relate to household buying behaviour, so we can not tell whether certain items are bought by different members of the family. This would have enabled a more detailed analyses to be undertaken where such as private label proneness could have been measured at the individual level. Scanner panel data enables an examination by actual purchaser which could be used in the future.

Small sample bases for some items made their examination difficult, and where appropriate these have been aggregated or left out of the average. This means that we focus on the larger and therefore more successful items, which may be thought to bias results. However, we already know something about market share effects with such as the Double Jeopardy pattern which can be taken into consideration in interpreting results from small sample bases. Even when small samples have been omitted from the average, their results have often been shown.

Those private labels examined in detail, Sainsbury, Tesco and Coop, are perhaps the most successful private labels. Others such as Liptons and Grandways have been examined only in so far as they are included in the OBPL category. These smaller private labels tend to be those of lesser quality and which are priced more cheaply. Therefore, the conclusions from this research could be said to favour the higher quality private labels. This needs to be borne in mind in interpreting the results.

8.4 OPERATIONAL LIMITATIONS

The models generally apply to the purchase of frequently bought non-durable consumer goods, such as grocery products and toiletries. Although the NBD has been applied on a limited scale to the study of semi-durable goods such as clothing (Ehrenberg 1972), the purchase of educational services (Ehrenberg 1979), industrial buying (Easton 1976, Easton 1979, Ehrenberg 1975) and now doctors prescribing behaviour (Stern 1990) and aviation fuel contracts (Uncles and Ehrenberg 1989),

more replication studies in these areas are desirable to test the scope of the models. This is particularly so for the Dirichlet model where replication studies have so far been more limited.

Such analyses would be interesting because private label are more successful in some product fields than others. For example, their share of the clothing market is much higher than for fast moving consumer goods, and generally lower in perfumes and cosmetics. So far our analyses have been limited to grocery product fields which rather limits the interpretation of our results. Other product fields need to be examined to be able investigate the nature of private label market shares.

In this study we did not consider the locational components in defining various populations at risk, nor in describing private label choice. In the present study, no data is available on the location of the panel member or the store visited. Such detail may in future be incorporated using scanner panel data. This would enable us to determine to what extent spatial factors affect a families's store repertoire, and measure each store's population at risk more precisely. Though much work has been undertaken on catchment areas, this has mainly been for towns and shopping centres rather than store chains throughout a region. Indeed the method of estimating the population at risk used in Chapter 5 could be more widely used to measure the size of the catchment area rather than its geographical boundary.

Relationships with other marketing variables have not been directly considered. These may be important in relation to private label purchasing because of perceived price, promotional and value for money differences. Also consumer attitudes to private labels would benefit our understanding of their purchasing patterns. Future analyses could develop these explanatory issues further to help our understanding of private label purchase behaviour.

We only consider choice for one or two product fields at a time whereas in practice shopping for a variety of product fields is undertaken. It is important to consider the buying of more than one product class in further work so that any inter-relationships between items can be examined. This is particularly interesting in relation to general and specific private labels proneness. For example, it may be that people are private label prone in some product fields, such as household items, rather than foods. Retailers would be interested in identifying any umbrella effects from their private label ranges.

Brand and private label choice is influenced by many factors, none of which are investigated in these analyses. Although their investigation was not necessary for these analyses directly, they nevertheless would add much to understanding why people buy private labels in the way they do.

8.4 FURTHER WORK

Research is a continuous process of knowledge accumulation. The discovery of new facts requires further understanding and explanation, and so the cycle continues. This study has mainly contributed empirical knowledge to certain aspects of private label buying behaviour not hitherto examined. However, there is much scope for developing these early results further.

The **population at risk** estimate could be developed further to provide retailers with a standard empirical means of assessing their catchment areas at the store chain or even single outlet level. This could then be used to compare the relative performances of units and used as a control measure. It also shows another application of the Dirichlet model.

The **repercussions of deviations** on other buyer behaviour measures requires further study. This would provide an insight to the inter-relationships between the various measures which would help us to use the models in a more diagnostic manner and appreciate their limitations. The high private label purchase rate is one of the first detailed investigations of a consistent model deviation. There are some other consistent and sizeable product field deviations from the models; period to period buying in particular was found to be deviant with no obvious explanation; also, sole buying patterns are on the whole less well predicted by the Dirichlet model.

Private label proneness is an area with many practical implications. Though there are few signs of this in the two product fields studied, others need to be examined to substantiate the result. Determining whether a private label "umbrella effect" exists throughout the store would be something of much practical use to the retailer. Indeed, a comparison of private label proneness with the same for brand names which exist in more than one product field would enable a direct comparison to be made and no doubt raise some interesting branding issues.

The fact that **private labels** are so successful in the store is worth further exploration. We have only examined their performance in two product fields. More studies are needed so that regularities can be identified which may then provide

pointers as to why they are so successful. Such results could then be compared with a similar study for brand leaders.

A longitudinal study of the introduction of a private label would enable us to examine the effects on brand and store choice behaviour. For example, data is available for Asda stores before and after the introduction of its private label range. Given that we have now shown that the models can be used as a benchmark for private label buying behaviour, we can compare the effects, if any, of launching a private label, on other brands and buying patterns generally. It is important that both manufacturers and retailers are aware of the repercussions of launching a private label on other items within the store. This would also show something of a dynamic situation where research to date is rather limited.

Purchasing across many product fields to examine the basket of groceries is an area of much practical importance to retailers. We know much about buying in one product field, and now something of buying across two. These foundations should be developed further.

The within-store analyses have been limited to store chains. It would also be interesting to examine the robustness of our results by individual stores and store types. For example, if private label shares vary by store outlet or type, the retailer could identify which stores were under and overperforming with respect to private labels and use the information to help monitor the business at the local level. Such information would also be valuable for refining private label strategy.

8.6 SUMMARY

As with any piece of research, there are some limitations in this research. The models used are based on assumptions about the real world which need to be largely fulfilled and appreciated; panel data is used for only a small section of grocery product fields which limits the scope of our findings; and there are various operational limitations which further work can address so as to enrich these results.

However, though these limitations affect the scope and nature of our interpretations, as long as they are borne in mind we can draw some interesting conjectures in the discussion section of Chapter 9. Now that regularities of private label buying behaviour have been identified, there is much scope for further work to enrich these findings and enhance our understanding of private label buying behaviour.

CHAPTER 9 : CONCLUSIONS AND DISCUSSION

9.1 Introduction**9.2 Summary Of Thesis Results****9.2a Empirical Results****9.2b Theoretical Results****9.3 Discussion****9.3a Retail Strategy****9.3b Branding****9.3c Population At Risk****9.3d Application Of Data And Models Used****9.4e Market Share****9.4 Summary**

9.1 INTRODUCTION

There are three parts to this, the final chapter. First, the results are summarised; then the results are interpreted in the light of previous research; and finally the findings are discussed in respect of wider issues such as private label strategy and branding.

9.2 SUMMARY OF THESIS RESULTS

The two main objectives of this research are :

- (1) To establish how people buy private labels and identify whether there are any differences between this and the way in which people buy branded items.
- (2) To determine whether private labels provide retailers with a competitive edge in respect of how people buy them.

It is appropriate that greater emphasis should now be given to understanding how people buy private labels because of their importance in grocery retailing, and the fact that retailers use them as part of their retail strategy. Indeed, our interpretation of the results provides an indication of whether private labels achieve these objectives.

There is an implicit, albeit unstated, hypothesis that because of the many differences between brands and private labels, this somehow shows through in the way they are bought. For example, that even when private labels and brands have the same market share, a private label attracts more loyalty because it is unique to a specific store chain; that people have a tendency to buy certain store's private labels more than others; and that private labels buyers differ in their demographic and socio-economic make-up to brand buyers.

Buyer behaviour theory provides the analytical framework and the models provide the null hypothesis against which measures of buying behaviour for brands and private labels can be compared and contrasted.

The main results from each chapter are summarised below, with wider interpretation to follow.

9.2a Empirical Results :

Chapter 4: How People Buy Private Labels

- * **Despite the many differences between them, private labels are bought in much the same way as brands. The fundamental patterns of buyer behaviour which the models describe apply on the whole to private label purchasing.**
- * **This has been found in five product fields, two regions, in US data, for different length time periods, in data from 1984, 1985 and the late 1960's and early 1970's, and in purchasing across two combined product fields.**
- * **Patterns of period to period buying are similar; they both follow a positively skewed purchase frequency distribution with a slight surplus of light buyers and a shortfall of medium and heavy buyers on average; product field buying rates are much the same and in line with the theory; incidences of sole and duplicate buying are also similar as are rates of duplicate buying.**
- * **However, there are some important differences. The main one being that private labels have a higher average purchase frequency and lower penetration than both the average brand and than is predicted by the model. So even after allowing for their market shares, they are bought more frequently, but by fewer people than their branded counterparts.**
- * **The deviation is consistent in its direction, but its size varies. On the whole, it is equally split between b and w in both regions because with the Dirichlet model, an under-prediction in w is matched by an over-prediction in b . However, in London the private label w is much higher than predicted whereas in Lancashire model fit is closer.**
- * **The nature of the Dirichlet model is such that an under-prediction in w is compensated by an over-prediction in b within the same product field. So private labels have a low b and high w in comparison to the theoretical predictions, whereas the opposite occurs for brands. This shows something of the way in which the Dirichlet model describes an "average" picture rather than a limited "best fit" condition.**

- * This difference in the values of the components of the sales equation affects all theoretical measures of buyer behaviour because the model uses the product of b and w (sales) as input. Therefore, it is necessary to determine the reasons for this difference before we draw any conclusions from the results. Otherwise we cannot determine which results are "real" and which are a consequence of the high private label w .
- * This high private label purchase rate shows through in other observed measures. For example, the observed share of requirements ratio is high, as is the incidence of repeat buying and rate of sole buying.
- * Theoretical predictions are affected; the NBD directly takes into account each private label's high w so predictions are largely in line with the observations and the deviations are small. By contrast, the Dirichlet model highlights the difference because predictions are based on market share inputs for each individual item and the product field rather than b and w separately.
- * Not all theoretical predictions are deviant as a result. For example, the rate of product field buying is still closely predicted. Why some measures are affected and not others is important in our diagnosis of the discrepancy in chapter 5.
- * There are some other deviations from the models. Rates of sole buying by private label buyers are much higher than predicted and somewhat higher than for the average brand. Rates of repeat buying are also very slightly higher. Whether these are a direct result of the high private label w or are additional cannot be answered until we find an explanation for the high private label w .

Chapter 5 : An Analysis Of The High Private Label Average Purchase Frequency

- * The difference in the values of the components of the sales equation for brands and private labels affects the theoretical predictions. Therefore, it was necessary to determine why this difference existed before being able to interpret the results properly.

- * We found that the private label w is not necessarily an indicator of higher loyalty. Rather, it is a consequence of the way in which buyer behaviour measures are usually calculated. There is an implicit assumption in calculating penetration that all items are equally available. So the sample of continuous reporters, which comprises some 650 households, is the potential buying population for all items examined.
- * However, specific private labels are not as widely available as the majority of branded items, so the potential buying population is overstated. Some households in the sample have no access to certain stores, and are unable to buy the private labels sold there. Indeed, the distribution index, which is used as a proxy for availability, shows that for Fruit Squash in London, for example, the average brand has over 8 times the distribution of the average private label.
- * This is further compounded by the fact that even when a customer is in one store, she cannot buy another store's private label, whereas specific brands may be available at several of the stores visited. Thus private labels suffer from limited availability and the opportunity to buy them is reduced as a consequence.
- * The actual buying population is referred to as the "population at risk". This is overstated for private labels because no account is taken of the buying population with access. Differences in availability need to be taken into account in calculating penetration.
- * Penetration is usually calculated as the proportion of buyers who buy an item in a given time period out of the sample of continuous reporters. Because the buying population is over-stated in the case of private labels, their penetration is under-stated. This makes the purchase frequency appear high by comparison. We know this because penetration and purchase frequency are related by the simple equation, $w(1-b)$ is approximately constant. Therefore, b can only be deemed high or low in comparison with w .
- * To test whether this explanation accounted for the apparently high private label purchase rate, various analyses were undertaken. First, a

more relevant population at risk was estimated to try and quantify the extent to which private label penetration was underestimated. Then analyses were conducted so that brand and private label availability were more equal by aggregating all private labels into a mega-private label, and examining purchasing at the within store chain level. The expectation being that the high private label w would no longer exist when their availability was the same. Results from chapters 6 and 7 also support this explanation empirically.

- * The fact that limited availability causes the apparently high private label w rather than it being a feature of private labels per se is supported by other results. Corona is a small brand with a similar availability index to a private label and it too has a high purchase rate. When private labels are grouped into the OBPL category, their high purchase rate no longer exists. Though few analyses have been conducted on small items because of the problems associated with them, these two examples support the population at risk explanation.
- * It is not possible to measure the population at risk precisely. This is because purchase incidence is stochastic, so by definition even potentially heavy buyers may fail to come into the market during an analysis period, even though they are part of the population at risk. Also some buyers, who may be part of the population at risk, may choose not to visit a particular store for some reason. This non-buying element is therefore hard to measure with any precision.
- * Nevertheless, two empirical and one theoretical estimate was made so as to provide a spectrum of different populations at risk. Though the absolute estimates varied, they all showed that the population at risk for private labels was indeed smaller than the sample of 650. Also that of the three stores examined, Sainsbury had the largest buying population, followed by Tesco and then Coop.
- * Brands are also subject to some population at risk effects, but these are more limited than for private labels.
- * Analyses which compare brands with private labels need to take into account differences in their populations at risk. Otherwise private

label results are distorted by a low penetration in relation to the average purchase frequency. This in turn affects the model specifications so that theoretical predictions cannot be used as a benchmark in the usual way.

- * Other explanations based on the differences between brands and private labels were examined, but none seemed to explain the discrepancy convincingly. Differences in price, pack size and the demographic profiles of the buyers were examined. However, the latter two were similar for brands and private labels so cannot in principle account for the high private label w. Price differences did not vary in a manner which could account for the discrepancy.
- * Therefore, the evidence suggests that the high private label purchase rate is not a consequence of the item being a private label per se which attracts more loyalty, but is a result of their limited availability. Private labels do not attract more loyalty in respect of their penetrations and purchase frequencies, they are bought in much the same way as any comparable brand.
- * Having found a satisfactory explanation for the difference in the components of the sales equation, we can now compare how people buy brands and private labels having allowed for the differences in their populations at risk. This means we can investigate further the differences in the rates of sole and repeat buying which were identified in chapter 4.

Chapter 6: How People Buy Private Labels Within Store Chains

- * Analyses at the within-store level enable us to compare brands and private labels because their populations at risk are the same, being equivalent to the store's clientele.
- * Private labels are very successful within the store chain. For example, in the two product fields examined, they tend to be the within store item leader on 12 of 16 occasions. On average, they have 45% market share across the two product fields as compared to 29% for the average itemised brand. There are no private labels with market shares below 21% in the two product fields studied. This suggests that they

either achieve a sizeable market share, or that when they do not, they are delisted.

- * The brand leader in KwikSave achieves an average market share of 50%. This is below that achieved by the Sainsbury private label, 60%, but higher than achieved by the average private label, 45% and higher than for brands in stores where private labels exist. Therefore, these limited analyses suggest that private labels may displace the brand leader, but more work is needed to generalise the result further.
- * Some private labels are more successful than others in terms of their market shares. The Sainsbury private label in particular is the within-store leader in all four data sets with market shares varying from 41% to 75%. Neither the brand leader in KwikSave, nor those of other stores achieve such high market shares as the average Sainsbury private label. The Tesco private label is within-store leader in three of our four data set with an average market share of 44%; Coop is item leader twice with an average market share of 38%.
- * Private label shares vary unsystematically across both product fields and regions. For example, Sainsbury private label shares range from 41% to 75%. This is not accounted for by regional differences because its share of Fabric Conditioner is high in Lancashire, whereas for Fruit Squash it is high in London. Nor does their success depend on the number of competing brands because for Fruit Squash in Lancashire, the Sainsbury private label has a 75% market share despite there being 5 other brands available.
- * We show that people buy private labels in much the same way they do brands, and this is largely in line with the theory. As far as the number of people buying, the rate at which they buy, and buying from one time period to the next, private labels are bought similarly to brands. There are some differences in respect of sole and duplicate buying which we outline later.
- * Buying patterns in stores with private labels are on the whole similar to those in KwikSave. So the presence of a private label does not affect fundamental patterns of buying behaviour. There are some

market substitution effects as the private label is included in most peoples' repertoires, but once the market share is taken into account, the private label is bought much like any other similar sized brand in the store. This is in line with the theory of buyer behaviour.

- * People buy one store's private label in much the same way as any other, once market share differences are taken into account. So Tesco private label buyers do not comprise a more select group of heavy buyers than say Coop private label buyers. However, the Sainsbury private label seems to attract slightly more medium and heavy buyers than any other which suggests it may attract slightly more loyalty in this respect.
- * Even when population at risk effects are taken into consideration, private labels still seem to attract more sole buyers who buy more often than the average brand and more than is predicted by the Dirichlet model. In Chapter 4 the difference was large; the rate of sole buying was some 80% higher than predicted, though the incidence was much in line with the theory. In the within store analyses, the incidences are some 30% higher and rates 20% higher than predicted. This confirms that much of the difference in Chapter 4 was a result of the population at risk mis-specification.
- * However, only two product fields have been examined and more results are needed to generalise the result. On the basis of these two product fields, it seems that private labels attract more sole buying loyalty than the average brand and than is predicted from theory. Moreover, this "extra" loyalty is not at the expense of branded items, it is additional.
- * Though private labels attract more sole buying loyalty irrespective of their position in the store, so does the brand leader in KwikSave. However, this does not occur for the other three brand leaders in stores where private labels are present. This suggests that it is a private label characteristic rather than a brand leader effect. We discuss this in more detail in the Chapter 7 summary.
- * The incidence of duplicate buying by private label buyers is slightly

lower than predicted. However, the difference is small and occurs predominantly for Fruit Squash. On the whole people buy brands and private labels interchangeably and do so much in line with their market share levels. This means there is no sizeable market segmentation between brands and private labels.

Chapter 7 : How People Buy Private Labels Across Two Product Fields

- * Private labels are bought across two product fields (Fruit Squash and Liquid Fabric Conditioner) in much the same way as are brands, and purchasing patterns are similar to those in one product field.
- * The fact that purchasing across a combined product field follows a similar pattern to that in one may seem surprising given the different nature of the field studied. However, the rates of product field buying (W) for Fruit Squash and Fabric Conditioner are similar, and both are fast moving consumer goods which are available in a variety of stores where the consumer has to make a relatively low-involvement purchase decision. So the fundamentals of buying behaviour are similar and this is reflected in peoples' purchasing patterns.
- * Furthermore, the Dirichlet model assumes independence of purchase between all items, thus in the case of Fruit Squash and Fabric Conditioner, they are bought as though the only difference between them was their market share.
- * Deviations resulting from population at risk mis-specifications identified in chapter 4 are also evident in purchasing individual items across the combined product field. Private labels have a high purchase rate and share of requirements ratio, with high duplication between private labels of the same store. Once analyses are confined to purchasing across the combined product field within the same store-chain, these differences no longer exist. This adds further support to our population at risk explanation and shows that purchasing patterns across two product fields are similar to those in one.
- * The number of people buying, the rate at which they buy, their product field rates and their share of requirement ratios are similar for brands and private labels. This seems to be so when private labels

and brands are aggregated into a mega-item and when they are itemised.

- * In the within store analyses in Chapter 6 it was shown that private labels and the brand leader in KwikSave attracted more sole buying loyalty than the average brand and than was predicted by the Dirichlet model. However, this does not occur in purchasing across the combined product field.
- * When brands and private labels are aggregated into two groups, we find that on average the incidences of sole buying are in line with the predictions, but rates of sole buying are much lower. When analyses are confined to buying individual items across a combined product field within store chains, we find that larger items tend to attract more sole buying loyalty than smaller ones. This suggests that it is not private labels per se which attract more sole buying loyalty, but larger items generally.
- * Though initially these sole buying results seem to contradict the results from chapters 4 and 6, where private labels attracted more sole buying loyalty, on closer inspection this is not so. The reason why private labels attracted more sole buying loyalty than the average brand in the within store analyses (Chapter 6) was because we compared the average private label with the average brand. Private labels tend to have high market shares, whereas the average brand share is lowered with the inclusion of smaller brands. So it is probably a reflection of the size of the item rather than whether it is a brand or private label.
- * However, in chapter 6 we showed that three brand leaders did not attract this "extra" loyalty though the brand leader in KwikSave did, so the results are not consistent.
- * Because private labels tend to attract such high market share levels, they also attract more sole buying loyalty than predicted. But whether this is more than for any other large brand can not be answered from these limited analyses.

- * These sole buying results are inconclusive and further work is needed to resolve the differences. Other product fields need to be examined in order to identify any regular patterns. The fact that sole buying patterns are often poorly predicted by the Dirichlet model makes it difficult to interpret results anyway. However, it seems that all private labels attract more sole buying loyalty, irrespective of their position in the store. But so do some large brands. Brands with smaller market shares attract less sole buying loyalty than is predicted.

- * Combining purchasing across two product fields enables us to examine general and specific private label proneness in more detail. One might expect people who buy private labels in one product field to be more inclined to also buy them in another; and that people might be prone to buying certain store's private labels. However, there is only slight evidence of general private label proneness and this does not occur for brands. People buy the same store's private labels interchangeably, and much in line with their market share levels. Indeed, from the limited analyses undertaken, results suggest that having bought a specific store's private label in one product field, the buyer is then less inclined to buy the same store's private label in another.

Though the thesis is largely empirical in nature, there are also some theoretical results to note.

9.2b Theoretical Results

- * Despite the complex nature of private label purchasing, as with other fast moving consumer goods, many highly regular patterns have been observed. Furthermore, these regularities exist for both brands and private labels.

- * On the whole, the NBD and Dirichlet models describe how people buy private labels. Thus, the models can be generalised to a new data set which hitherto has not been examined to any great extent.

- * On some occasions though, model predictions are deviant. For example, sole buying patterns are generally poorly predicted by the Dirichlet model so too is the incidence of period to period buying by the NBD model. Although these are interesting theoretical points, they do not

directly affect our main brand/private label comparison because they occur for all items in the product field. This means the models can still be used as a yardstick, although this does make it more difficult to identify patterns. Further work should be undertaken to examine why these systematic deviations occur in order to learn more about the limitations of the NBD and Dirichlet models and the data.

- * The way the model fitted the components of the sales equation in chapter 4 was such that the deviation was more or less equal for b and w . Even though w was correctly specified, and b was artificially low, the Dirichlet model predictions were deviant for both. This is because the model uses market shares and then apports values of b and w .
- * The models describe buying patterns within product fields, within store chains, between store chains and across combined product fields. Though many studies have been undertaken on product field purchasing, few have focussed on buying at the within-store level. This study provides further empirical results. The models also describe purchasing across two product fields. This is a new result with much promise for further work on the interaction of purchasing behaviour across many different product fields. It also enables us to focus more on general and specific private label proneness across product fields.
- * The models are robust. In seasonal product fields, they still describe buying patterns to a first order of approximation. When the components of the sales equation differ for brands and private labels they can still be used, albeit in a more diagnostic manner. They apply when purchasing is confined to one product field and across two, when one is examining store choice, brand choice and private label choice.

We now discuss the thesis results.

9.3 DISCUSSION

Private labels have received so much attention in the marketing literature primarily because of their success in the grocery sector. However, the majority of studies have focussed on three issues: consumer perceptions of the differences between brands, private labels and generics; socio-economic and demographic characteristics of private label buyers and whether private labels increase store loyalty. There has been no systematic research on how people buy private labels. Furthermore, much of the research has been ad-hoc in the sense that findings have not been brought together. Rather the fashion has been to use different methodologies and data sets to examine the same issues.

This research has established how people buy private labels and identified whether there are any differences between this and the way people buy branded items. It has also helped determine whether private labels provide the retailer with a competitive edge in respect of how people buy them.

We have shown that on the whole people buy private labels just like any other brand. We now discuss the implications of this result further, bringing in past research findings where appropriate.

9.3a Retail Strategy :

Retail competition is no longer based solely on price. It is now more about attracting customers on the basis of a distinct store image. This includes factors such as store location, atmosphere, product range, prices and service. Retailers use private labels to play an integral part in developing this distinct store image by offering something unique to the customer. Private labels are expected to differentiate the retailer from his competition and this somehow feeds through into market share and profits.

To date retailers have had limited information on how their customers buy their private labels and those of other stores. The results from this study can be used to help bridge this gap.

In Chapter 1 (page 24) we outlined various objectives which private labels were expected to achieve. Private labels are used to differentiate one retailer from another in such a way that they build a competitive advantage (Frank and Boyd 1965, Leahy 1967); they are used to build and sustain store loyalty (Simmons and Meredith 1984, Dunn and Wrigley 1984, Leahy 1987); and to

capitalise on the familiar umbrella name as customers are specific private label prone (Rao 1969a). In addition, other objectives relate to operational control, but since these have not been addressed in this study we concentrate our interpretation on those detailed above.

For private labels to be a successful differentiating tactic, they must either appeal to a different type of person to brands so as to widen the store's clientele, or be bought differently to brands so as to increase loyalty for example.

Past research has concentrated on trying to show that private labels are indeed different to brands in terms of the components of the marketing mix and the type of people who buy them. Much of this research has concentrated on trying to show that private label buyers are different to brand buyers in terms of their demographic and socio-economic profiles. If private label buyers were somehow different to brand buyers, not only could the retailer target more effectively, but the manufacturer could produce brands which did not attract the same type of people who bought his private labels, thus minimising any cannibalisation effects.

The weight of evidence suggests that although there are some slight differences between brand and private label buyers, these are not sufficient to constitute an identifiable market segment. Differences have been found in that private labels buyers have higher consumption rates, larger households, younger housewives with children, are more up-market, have higher incomes, higher education, and also that men shoppers are more inclined to buy private labels (Massy, Frank and Lodahl 1966, Frank et al 1967, JWT 1970, Mintel 1976, Retail Business 1971, Wrigley and Dunn 1984b). However, other studies have found there to be no consistent evidence that private label buyers differ from brand buyers (Frank and Boyd 1965, Munn 1960, Myers 1967). Analyses have been undertaken in this research on demographics such as age of housewife, social class, number of children and housewife working status. These show that brands and private labels are on the whole bought by the same type of people.

Peoples' perceptions of the perceived risk associated with brands, private labels and generics have been shown to differ. Perceived risk is the expected negative utility associated with the purchase of a particular item (Bauer 1960), so all purchases carry some degree of perceived risk. Brands are perceived to

be higher in quality and more expensive; private labels are moderately priced and of medium quality; and generics are lower quality discount alternatives (Faria 1979, Granzin 1981, Murphy and Laizniak 1979, Rosen 1984, Wheatly and Jones 1983, Belizzi et al 1981, Cunningham, Hardy and Imperia 1982). In a PhD study (Chernatony 1988), it was found that across 6 product fields, consumer perception is always brand versus private label/generics. He concludes that retailers marketing of private labels has not yet reached the point where they have moved sufficiently up-market to be considered similar to brands. Whether this affects their purchase behaviour is another matter.

Though people may perceive private labels to be different to brands, this does not seem to be reflected in their purchase behaviour. Private labels seem to be bought by the same type of people as those who buy brands which is not surprising in as far as people buy brands and private labels interchangeably. There is no such thing as a hard-core of only private label buyers in the time periods examined in the thesis.

Private labels do not therefore seem to be bought by different types of buyers to brands. So to act as a successful differentiating tactic requires that they are bought differently from brands. However, the main conclusion from this research is that private labels are bought much like any other brand of a similar size.

There is a slight sign that private labels attract more sole buying loyalty than brands. However, this may be more a result of their high market share levels as it also occurs for some of the large brands. There is also some slight evidence that people are "general private label prone", rather than being prone to buying specific stores' private labels. There is no sign of any difference between buying patterns in or between stores which offer private label and KwikSave which does not, though more work is needed here as KwikSave is our only example of a store without private labels.

These results are much in line with past research where a variety of measures have been used to measure loyalty. Some have succeeded in capturing one dimension, others are indexes which try to capture some elements of its multi-dimensionality (Cunningham 1961, Carman 1970, Enis and Paul 1970). Most of the research has tried to find a link between brand loyalty and store loyalty.

For example, Cunningham used the Chicago Tribune panel where the purchase histories of 491 households in 44 product fields were monitored in 1961. Though he identified private label loyalty in a given product class, he put forward no evidence for this leading to high store loyalty. He stated that private label loyalty had an equal chance of existing among low store loyal and high store loyal housewives. Similarly Rao (1979a) found that the higher a housewife's store loyalty, the greater the chance of her purchasing private labels. Overall it seems that private label purchasing is partly determined by, rather than a determinant of, store loyalty.

Though the retail environment has changed since the 1960's, this does not seem to have altered these conclusions. For example, studies using stochastic models and panels data have shown that brand and store loyalty is low, and furthermore that because of low purchasing rates, loyal buyers are not commercially attractive anyway (Kau and Ehrenberg 1984, Wrigley and Dunn 1984b, Uncles and Ehrenberg 1988, Ellis and Uncles 1989, Lamb 1989).

It seems that private labels are bought by the same types of people as are brands, and they are bought in a similar manner with only a slight indication that they attract more sole buying loyalty. So in this respect retailers do not gain a competitive advantage from offering private labels. Furthermore, as all private labels attract slightly more sole buying loyalty, it is hard to see which, if any, retailer gains.

However, retailers might still achieve operational benefits from offering private labels. Indeed, the private label does not have to achieve anything more than another brand to be worth stocking. The fact that they achieve such high market shares within the store provides the retailer with room for delisting minor brands if so desired. They might also lead to higher profit margins, greater operational control and are a vehicle for new product development.

9.3b Branding

Marketing theory and practice has long centred around the value of branding. Indeed it was widely believed that private labels would fail because they would be unable to compete with brands because they were seen to be somehow inferior to brands. The fact we have shown that on the whole they are bought similarly to brands, and seem to attract slightly more sole buying loyalty, raises some interesting branding issues which we now consider.

Traditional marketing theory regards a brand as being an added value entity which portrays a unique and distinctive personality. One ingredient for a successful brand is the benefit to consumers of added values. To establish a positioning for specific brands in consumers minds, and communicate the added values, advertising is necessary. Advertising helps establish the brand as a unique bundle of values without a directly similar counterpart that consumers can directly substitute. So by using several elements of the promotions mix, a brand is developed which adds up to something more than the technical features of the product (King 1970).

There are two points to raise here. First, one might expect that private labels would be bought differently because they are not branded in the traditional sense. Secondly, even if there are no differences here, they should achieve a lower market share than a branded item.

There is no evidence that consumer purchasing patterns reflect the differences marketers try and develop. Though marketers perceive their brands to be unique and therefore not directly substitutable, we find that people buy brands and private labels interchangeably. Indeed, we find that items are bought as though they were no different in anything except their market shares.

All this might seem surprising because private labels differ from brands in most aspects of the marketing mix. They are not directly advertised unless part of a corporate advertising campaign, though they are extensively promoted within the store. Their availability is limited to individual store chains which means they are more difficult to buy than the average brand. They tend to be cheaper than brand leaders but more expensive than smaller brands.

Yet empirically we show that despite these "shortcomings", private label purchase behaviour is closely predicted by the models and furthermore they perform better than those brands examined in respect of their market shares. Though only two product fields, and two regions were examined, the results are consistent. Indeed, private labels achieve a higher market share than most brand leaders within the store. This suggests that the combination of marketing inputs which make up private labels is more successful than that which comprises brands. It is not possible to try and interpret this in the light of individual elements of the marketing mix because consumers essentially buy a combination of all mix factors. Nevertheless, one can propose some interesting

conjectures here.

For example, despite Fabric Conditioner, Baked Beans, Instant Coffee, and Washing Up Liquid brands being advertised, they achieve lower shares within the store on average than do their respective private labels. This could mean that; advertising is ineffective in building a brand's market share; that the effects of advertising are over-powered by in-store promotions which are biased towards private labels; that store advertising is more effective than brand advertising in the context of grocery shopping; that brand advertising boosts product field purchasing, but in-store promotional effects are stronger; that brand advertising encourages people to switch between the different brands more regularly and somehow private labels benefit from this brand dis-loyalty.

So just because private labels fail to fit the marketers definition of a brand, as outlined by King (1970), does not mean they are unbranded. Indeed, it could be argued that retailer names are brand names in their own right. Even our analyses of data from 20 years ago showed that some store's private labels were successful. More recently retailers have committed resources to developing a distinct corporate identity and are as well, if not better known, than the largest manufacturer brands.

9.3c Population At Risk

It was not possible to quantify the population at risk precisely though a reasonable estimate has been made. Manufacturers and retailers need to have some idea of the size of the population at risk for their particular brand or private label as the greater the population at risk the higher the sales potential of each store chain.

Using the Dirichlet model to provide a norm for each store's population at risk may be of use to retailers and manufacturers who currently use catchment area information and store modelling scenarios. The method used in Chapter 5 recognises that not only are private labels available in a limited fashion, but also that when a customer is in one store, she can not buy the other stores' private label. This is something which has not been bought out of the geographical literature specifically.

9.3d Appreciation Of The Data And Models Used

If no adjustment is made for private labels limited availability, results are likely to be mis-interpreted. So it is important to understand the limitations of both the models and the data used in any research.

9.3e Market Share

The existence of buying patterns is independent of the degree of item differentiation and the number of items in the market. Fast moving consumer goods markets with their heavily advertised brands and unadvertised private labels are often cited as classic examples of product differentiated markets. The effects of all such factors are subsumed in the distribution of market shares between the various items.

Perhaps the most intriguing question from these analyses is why the models can describe brand and private label buying patterns so well? And why market shares are distributed as they are? Even when there are differences in respect of the marketing mix elements, market share still captures the basic market structure.

In each region the fundamental retail situation is similar with a selection of retail outlets, a public transport system, and a population of buyers. Grocery products tend to be bought in accordance with their usage, and people tend to shop weekly. So there is a certain uniformity in the demand side which may account for the similarity of buying patterns found in fast moving consumer goods markets generally. Market shares reflect peoples actual preferences in the aggregate. Each consumer has a preferred set of items from which to choose and the item which is favoured by the most people is by definition the "brand leader".

9.4 SUMMARY

Despite the many differences between brands and private labels, private labels are bought in much the same way as any other brand with a similar market share. Though retailers have been using private labels to achieve various objectives aimed at differentiating their store chain from the competition so as to help develop a competitive advantage, we find little evidence that people buy private labels in such a manner as to achieve these objectives. There is a slight indication of heightened loyalty to private labels, but this occurs for all retailers.

However, the success of private labels can not be ignored. They are often the within-store item leader and form an integral part of many peoples' repertoires despite lacking many of the traditional attributes of branding.

APPENDICES

- 1 Example Of Self-Completion Diary For Panel Data
- 2 Brand And Private Label Categories Analysed
- 3 Stores Used In The Analysis
- 4 An Outline Of Some Of The Stochastic Models Of Buyer Behaviour
- 5 Table Of "A" Parameter Values
- 6 Distribution Indexes For Fruit Squash Lancashire, Fabric Conditioner London and Lancashire (48 weeks)
- 7 Distribution Index For Fruit Squash London For A 24 Week Time Period
- 8 73 TCA Product Fields
- 9 An Analysis Of The Dirichlet "S" Parameter
- 10 Uncles, M.D. and Ellis, K., (1989), The Buying Of Own Labels, European Journal Of Marketing, volume 23, number 3, p 57 - 70.
- 11 Uncles, M.D. and Ellis, K., (1989), Own Labels: Beliefs And Reality, in Retail And Marketing Channels, Economic and Marketing Perspectives on Producer-Distributor Relationships, eds, Pellegrini, L. and Reddy, S.K.
- 12 Ellis, K. and Uncles, M.D., (1989), How Private Labels Affect Consumer Choice, in Food Choice and Opportunity, ed. Beharrell, B.
- 13 Incidence Of Duplicate Buying For Biscuits (48 weeks 1987)

APPENDIX 2 : BRAND AND PRIVATE LABEL CATEGORIES ANALYSED

Fruit Squash

London & Lancashire

Brands

Quosh
 Corona
 Robinsons
 Robinsons Barley
 Kia-Ora

Wells
 Roses Lime Juice
 Sunquick
 Vimto
 Gollicrush
 Sunland
 Gee Bee
 St. Clements
 Other Brands

} OB

Private Labels

Coop
 Sainsbury
 Tesco

Spar
 Fine Fare
 Sunshine
 Presto
 Dee
 Asda
 St. Michael
 Other Private Labels

} OBPL

Liquid Fabric Conditioner

London & Lancashire

Brands

Comfort
 Lenor
 Softlan
 SoSoft

Formula 77
 Soft & Gentle
 Other Brands

} OB

Private Labels

Boots
 Sainsbury
 Coop
 Tesco

St. Michael
 Asda
 Other Private Labels

} OBPL

APPENDIX 3 : STORES USED IN THE ANALYSIS

Asda	
Boots	
Coop	*
Fine Fare	
Dee	
Hillards	
International	
KwikSave	*
Marks and Spencers	
Morrisons	
Presto	
Safeway	
Sainsbury	*
Spar	
Tesco	*
Waitrose	
Others	

* examined in Chapter 6.

APPENDIX 4 : AN OUTLINE OF SOME OF THE STOCHASTIC MODELS OF BUYER BEHAVIOUR

This appendix provides an outline of some stochastic models of buyer behaviour which have been tested over the years. We discuss the simple Bernouilli type models of the 1950's and 1960's and show how modelling has developed into the more sophisticated explanatory models of the 1980's. The reasons for choosing the NBD and Dirichlet models for our analysis of private label buying behaviour are given in chapter 2.

The appendix consists of four parts. First, we examine the early models and then the various extensions to these; then more complex brand choice and purchase incidence models are discussed, leading finally to more recent comprehensive models.

Of the ten reviewed here, only two are used in the thesis. These are the Negative Binomial Distribution (NBD) and Dirichlet models.

4.1 BASIC MODELS

4.1a Bernouilli Model

This simple distribution is often used as a base distribution in the same way as the Poisson is used in the NBD, rather than a stand alone model. Purchase decisions are assumed to have only a dichotomous choice ie brand A, B, or vice-versa. A Bernouilli occurs if the outcome is either one or the other.

There are three assumptions:

A zero-order process. In any purchase decision the consumer will have a certain probability of purchasing a particular brand which is unaffected by previous purchase decisions. Under these circumstances there is no purchase event feedback. This assumption still causes much debate in the literature and there is evidence both for (Frank 1962, Blattberg 1979, Jeuland, Bass and wright 1970, Bass, Givon, Kalwani, Reibstein and Wright 1984, Givon 1984, Kahn, Kalwani and Morrison 1986) and against (Kuehn 1962, Wierenga 1974, Givon and Horsky 1978) its occurrence in practice.

Purchase probabilities are assumed to remain unchanged over time so that nothing the consumer does or is exposed to alters the probability of purchasing

the brand. This means that such as advertising and promotional effects have no apparent influence on the individual.

The population is assumed to be homogeneous, which is rarely the case in reality.

These basic assumptions are restrictive and as a consequence various extensions of the process have been made. One in the form of a compound Bernouilli which makes explicit the assumption of population heterogeneity. In this case each consumer has a different probability of buying the brand, but these are still unaffected by past purchasing decisions.

Early tests (Brown 1953, 1965) using the Chicago Tribune panel for coffee, concentrated orange juice, soap and margarine were successful. Givon and Horsky (1978) results showed that the Bernouilli was a good descriptor of a substantial part of the population, but not all of it. There remains a significant number of consumers who can not be well described by the zero-order process. Wierenga (1974) studied Dutch panel data for an unnamed food product, beer and margarine at the individual level using binomial test runs. He found evidence of a substantial amount of non-Bernouilli behaviour for all three brand categories.

4.1b Stationary Markov Models

These can be more complex than the former. Some incorporate the effects of past purchases on the probabilities of the current purchase. The number of previous purchases which affect the current one is called the 'order' of the model. First-order models only consider the influence of the last purchase on the current decision. However like the Bernouilli, they still assume stationarity and population homogeneity.

These have been widely criticised on a number of grounds, particularly in respect of the lack of empirical support (Ehrenberg 1965, Massy and Morrison 1968). For example, there is evidence that the brand choice decision is affected by more than one past purchase (Kuehn 1958). Also the model assumes that all consumers have the same transition probability matrix, which is contrary to empirical evidence.

Various extensions to the basic model have arisen as a means of overcoming

such criticisms. Non-stationarity Markov models exist. For example Lipstein (1959) proposed a model where the transition matrix was non-stationary, but he encountered many operational problems. One area where success was achieved was in brand launch situations. Harary and Lipstein (1962) used the non-stationary Markov model to measure how new brands evolve in the test market. It has also been successful in product switching applications (Styan and Smith 1964).

4.1c Linear Learning Models (LLM)

This was developed by Kuehn (1962). The underlying feature is that consumer brand choice is always affected by past brand choice ie that purchase event feedback exists.

This differs from the Bernouilli where past purchases have no effect, and to Markov models where only certain purchases have any influence. Moreover, with LLM models the relationship between the pre and post purchase is linear.

The model also assumes quasi-stationarity in the sense that parameters do not change over short periods of time. Also the population is assumed to be homogeneous so that all consumers will have the same parameters.

Another important characteristic is that the purchase probability never goes above or below a certain point. This means consumers do not develop such a strong preference/rejection for a brand as to ever completely accept/reject it. However in reality some consumers are 100% loyal in a relatively short time period, whilst other brands are excluded from a consumers repertoire (Ehrenberg 1988).

Other more operational criticisms have also been made. First, parameter estimation is difficult which means its use is limited. In addition treating brand choice in such a dichotomous manner, akin to the Bernouilli situation, also limits its usefulness. The model requires a fixed number of purchases for testing which causes problems because people take different lengths of time to use up their purchases. For example, a heavy buyer may take only half the time to generate 10 purchases as a light buyer. The population is also assumed to be homogeneous which is erroneous.

One area of debate concerns the learning/contagion issue. Kuehn (1958) proposed that there was a learning effect so that consumers purchase

probabilities would change over time in accordance with their experience from previous purchases. He tested coffee purchases and found the zero-order process could only be rejected for 25% of families at the 95% confidence limit.

Frank (1962) developed a counter-hypothesis. He suggested what Kuehn has interpreted as learning, was in fact "spurious contagion". Changes in consumer purchase behaviour are the result of inherent population heterogeneity rather than learning effects. He applied the Bernoulli to each household separately as a way of dealing with heterogeneity. This assumes that their brand choice probabilities were likely to differ from one another. He found that a substantial part, but not all, of these learning effects reported by Kuehn could be accounted for by population heterogeneity.

Despite these criticisms, the model has been applied to some brand choice situations. Massy (1970) tested the model on brand switching behaviour and found it fitted well for orange juice and toothpaste but less so for coffee and beer. Carman (1970) fitted the model to aggregated data and found the LLM fitted the data well. Rao (1969b) tested the model on store choice behaviour and found the probability of a housewife purchasing a product in an outlet is higher the more often and more recently she purchased it from there in the past. Thus adding weight to the purchase event feedback issue. Rao's data was then used by Aaker and Jones (1971) for toothpaste, paper products and coffee. Coffee was poorly predicted probably because there were more private labels in the product field, and so brand choice would be interrelated with store choice. They further substantiated the purchase event feedback claim by showing that purchase probabilities were higher the more times the shopper visited the store.

4.2 VARIATIONS OF THE BASIC MODEL

4.2a Composite Heterogeneous Brand Choice Model

This was developed by Jones (1973). He proposed that individual consumer behaviour is described by one of three models. The zero-order Bernoulli, first-order Markov or linear learning model. A certain proportion of the population is assumed to behave in each of the three ways so as to incorporate population heterogeneity.

This was tested on dentifrice, wax paper, head-ache remedies, facial tissues and liquid detergents. Overall he found that the more complex composite model

performed less well than the individual sub-models.

4.2b The Probability Diffusion Model (PDM)

This is still a zero-order model but the probability of choosing a particular brand may change between purchases. The model allows non-stationarity in brand choice but unlike the Markov and LLM this non-stationarity is not caused by purchase event feedback. Rather it is the result of events external to the model such as market activities etc.

Market Research Corporation of America (MRCA) panel data for toothpaste was examined and the fit was found to be good. When comparisons were made with other models the LLM performed better in more stable period whereas the PDM was best in unstable conditions.

4.2c The Negative Binomial Distribution (NBD)

This is a purchase incidence model which was originally developed to describe brand purchase incidence. It has been successfully used in buyer behaviour and store choice. More details are provided in chapter 3.

4.2d The Mixed Exponential Model

This was developed by Fournier and Woodlock (1960) to predict the penetration levels of new and frequently purchased consumer products and retail outlets. It has also been applied to estimating market shares of new products (Parffit and Collins 1968).

4.3 BRAND CHOICE AND PURCHASE INCIDENCE MODELS

4.3a The Dirichlet Model

The NBD concentrates on describing the purchase incidence of a single brand at a time. The Dirichlet is more flexible in that it can be used to provide predictions for a multitude of brands. The model was originally formulated by Chatfield and Goodhardt. It has since been successfully applied to store and brand choice behaviour (Ehrenberg 1988 Chapter 13, Kau and Ehrenberg 1984, Bass, Jeuland and Wright 1975, Uncles and Ehrenberg 1988, Lamb 1989, Lamb and Goodhardt 1989, Wrigley and Dunn 1984b, Ellis and Uncles 1989a Appendix 12). This model is discussed more thoroughly in chapter 3.

4.3b The CNBL Model

This is a complex stochastic model proposed by Zufryden (1978). It

incorporates three essential aspects of buyer behaviour vis purchase incidence, brand choice and population heterogeneity.

It results from integrating individual behavioural components forming a Condensed Negative binomial distribution of aggregate product class purchases; a Beta based distribution of individual brand purchase probability over the population of consumers and a LLM of individual brand choice. The resulting acronym is therefore CNBL.

The model provides such estimates as average market shares, cumulative product class penetration, distribution of individual brand choice probabilities over the entire population, cumulative brand penetration and repeat buying measures.

An empirical test on dentifrice produced a good fit and the model coped well with non-stationary conditions.

4.3c The Multiple Hypergeometric Model

This is essentially a modification of earlier models as developed by Chatfield and Goodhardt (1975), Ehrenberg and Goodhardt (1970), Bass, Jeuland and Wright (1975). It is an integrated brand choice and purchase timing model proposed by the latter group.

The important attributes of the model include:

- 1 The decomposition of the purchase process into a timing and choice process. Intervals between purchase occasions are distributed for individuals as Erlang of order r conditional upon the rate at which individuals purchase the product class. The distribution of this buying rate over the population is Gamma.
- 2 Modelling of individual behaviour and the incorporation of population heterogeneity. Individuals select brands according to a multinomial probability. The choice probability vector is then distributed Dirichlet over the population.
- 3 All brands in the product class are considered so that choice is a multi-nomial brand choice process. Under the assumption of independence between the purchase incidence and choice process, the two processes are then compounded.

An empirical test of this model on French cooking oil showed some success. For example, it produced good estimates of penetration but underestimated repeat buying and duplication.

4.4 EXPLANATORY MODELS

None of the models so far have incorporated market variables (advertising, pricing etc) as a means of providing some explanation for switching behaviour. This is largely because of the lack of appropriate data.

4.4a An Explanatory Model

Jones and Zufryden (1980) developed a potentially rich model which not only predicts brand choice and purchase incidence, but also provides some explanation for such behaviour.

The models consists of two basic components:

- 1 A logit model to explain brand choice probability as a function of purchase explanatory variables.

- 2 A poisson model is used to describe the purchase incidence behaviour of the product class. Moreover, both components also take into consideration the heterogeneous nature of the population of consumers.

The multivariate brand choice component has the following assumptions. Each consumer has a different probability of buying a particular brand for different values of a set of explanatory variables that influence brand choice. These probabilities assume a Beta distribution over the population. The probabilities are independent of past purchase outcomes and constant over time in the absence of changes in the vector of explanatory changes. The expected value is defined by a logit model.

The purchase incidence component follows work by Ehrenberg (1959). It is assumed that the number of individual consumer purchases of a product class over a specified length of time is distributed in a Poisson form. Different consumers are assumed to have different values. This population heterogeneity is expressed by a Gamma distribution. Finally, it is assumed that the product class purchase incidence is independent of brand choice and the set of

explanatory variables.

Empirical tests have been undertaken. The explanatory variables were categorical (though continuous variables are allowed) and confined essentially to demographic characteristics. The model was a good fit.

The major problem in using the model is that it requires complex estimation procedures. Although much panel data also has records of demographic characteristics, data on sales promotions and advertising etc would involve greater data collection efforts.

Zufryden (1987) has since built a model which relates the distribution of exposures from a brands media schedule to brand purchase. The test was successful.

4.4b Simulation Models

These are capable of incorporating a multitude of variables and building various forms of relationships from them.

The discussion here is concerned with micro-analytic simulation models which attempt to describe individual behaviour. The market behaviour is then achieved by aggregating individual behaviour. One example of such a model is NOMAD. This was specifically developed to simulate the buying of frequently purchased consumer non-durable goods.

NOMAD Model

This was developed by Cook and Herniter (1971) for three purposes: to forecast demand, to evaluate marketing influencing policies and to monitor competitive behaviour.

The basic unit of analysis is the individual consumer. The basic action is the purchase of the product. These individuals are then aggregated to provide a picture of the total market behaviour. The model is designed to predict purchase behaviour of up to 500 consumers over 50 time periods in a well defined market with up to 10 brands or stores.

As input each consumer is assigned an aggregate purchase frequency, a time between purchase interval and a satisfaction level which determines brand

switching.

Brand choice behaviour can be affected by learning effects (purchase experience, price changes, advertising etc), time effects (forgetting, rate of decay etc) and a new brand introduction effect. Each are assumed to exert different degrees of influence on individual consumers.

Empirical tests were conducted on two product fields, aluminum foil and cold tablets. The results were only satisfactory in predicting repeat purchase rates.

4.5 Summary - Differences Between The Various Models

Stochastic models of buyer behaviour differ mainly in respect of their treatment of population homogeneity, stationarity and the effects of past purchases. These are discussed briefly below.

Homogeneous or Heterogeneous Population of Buyers

The question here is whether consumers are inherently different from each other in terms of their behaviour ie population heterogeneity, or are do they all behave in the same way ie population homogeneity.

Models vary in their treatment of this. From the simple Bernouilli, which assumes that all individuals are the same in terms of their purchase behaviour, to the more complex Dirichlet and NBD models where an a-priori Gamma distribution reflects population heterogeneity in frequency of purchase.

There are three ways to take account of heterogeneity. First, certain determinants of purchase probabilities can be identified and built into the model. This requires data on each factor to be obtained from each consumer used in the sample. Secondly, household specific determinants of buyer behaviour may be identified and data on them collected. For example, separate models can be estimated for light and heavy buyers. Thirdly, certain key parameters of the buying process may be assumed to vary by household. For example, that individual purchase probabilities follow a Poisson process, but with different means.

Stationarity or Non-Stationarity

In a simple stochastic model the individual is described by a set of probabilities which reflect the likelihood of choosing any particular brand on

the next purchase occasion. For example, purchase probabilities of 0.9 and 0.1 for brand A and B mean the consumer is 90% likely to choose brand A and only 10% likely to choose brand B. Therefore the particular brand chosen is neither wholly predetermined nor is it a matter of pure chance (ie 50/50).

With models such as the Bernouilli, it assumes that the individual's purchase probabilities remain unchanged over time. This has received much criticism and other models have purchase probabilities which vary over time. Changes can be the result of learning and/or marketing influences.

Probabilities can vary by consumers in a heterogeneous population, and/or by time. Some models incorporate an a-priori distribution to reflect consumer heterogeneity such as the Gamma part of the NBD. With other models such as the Linear Learning Model (LLM), purchase probabilities vary over time in accordance with a consumers past purchases.

There is now much interest in trying to model dynamic situations. The inclusion of marketing variables such as advertising and promotions (Zufryden 1978, Jones and Zufryden 1980, Jeuland 1979) is a move towards understanding marketing dynamics.

Purchase Event Feedback

Some models assume the act of purchasing has a direct influence on the households subsequent probabilities. The LLM, for example, assumes purchase probabilities are affected by all previous purchases weighted so that the most recent has the greatest effect. In contrast, zero-order Markov processes assume no effect from past purchase behaviour. Others such as first-order Markov models assume the last purchase influences the decision. The Dirichlet assumes no purchase event feedback in stationary markets, but this may not apply in non-stationary conditions.

There is considerable support for zero-order processes (Frank 1962, Bass, Givon, Kalwani, Reibstein and Wright 1984, Givon 1984, Jeuland 1979, Kahn, Kalwani and Morrison 1986). The assumption of past purchases not influencing future purchase probabilities has some appeal. This zero-order property more importantly has substantial empirical support. However significant empirical research has been presented both for and against this theory. The conclusions are unclear. For example, Massy, Montgomery and Morrison (1970) have

replicated some of these studies in order to try and determine the validity of purchase event feedback. They concluded that zero-order processes exist in some product fields and not others. What the differentiating factors are here, is unclear.

In summary, stochastic models vary from the most simplistic buying scenarios to those which try and cater for a more realistic buying situation.

Early models such as the simple Bernouilli distributions assumed zero-order processes, fixed probabilities and a homogeneous population. Various extensions have been made to these basic assumptions to reflect a more realistic buying process. Some researchers have attempted to use elements of each basic model and developed composite models. Attempts have also been made to fully integrate these models so as to match the comprehensive verbal theory proposed by Howard and Sheth. Here market variables have been included in an attempt to explain the process rather than see it simply as a descriptive tool.

APPENDIX 5 : TABLE OF DIRICHLET 'A' PARAMETER VALUES

Table B3. Values of the NBD and LSD Parameters a (Adapted from Chatfield [1969])
NBD: Values of $a = m/k$ for various values of $c = -m/\ln p_0 = -wb/\ln(1-b)$.
LSD: Values of $a = q/(1+q)$ for various values of w .

	Values of c for the NBD or w for the LSD									
	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1	0.00	0.21	0.43	0.66	0.89	1.14	1.40	1.67	1.94	2.22
2	2.51	2.81	3.11	3.42	3.73	4.05	4.37	4.70	5.03	5.37
3	5.71	6.06	6.41	6.76	7.12	7.48	7.85	8.22	8.59	8.97
4	9.35	9.73	10.11	10.50	10.89	11.29	11.69	12.09	12.49	12.89
5	13.30	13.71	14.13	14.54	14.96	15.38	15.80	16.22	16.65	17.08
6	17.51	17.94	18.38	18.81	19.25	19.69	20.14	20.58	21.03	21.48
7	21.93	22.38	22.83	23.29	23.74	24.20	24.66	25.12	25.59	26.05
8	26.52	26.99	27.46	27.93	28.40	28.87	29.35	29.83	30.30	30.79
9	31.27	31.75	32.23	32.72	33.20	33.69	34.18	34.67	35.16	35.65
10	36.15	36.64	37.14	37.64	38.14	38.64	39.14	39.64	40.14	40.65
11	41.15	41.66	42.17	42.68	43.19	43.70	44.21	44.73	45.24	45.75
12	46.27	46.79	47.31	47.82	48.35	48.87	49.39	49.91	50.44	50.96
13	51.49	52.01	52.54	53.07	53.60	54.13	54.66	55.19	55.73	56.26
14	56.80	57.33	57.87	58.41	58.95	59.48	60.02	60.57	61.11	61.65
15	62.19	62.74	63.28	63.83	64.37	64.92	65.47	66.02	66.57	67.12
16	67.67	68.22	68.77	69.33	69.88	70.43	70.99	71.54	72.10	72.66
17	73.22	73.78	74.34	74.90	75.46	76.02	76.58	77.15	77.71	78.27
18	78.86	79.40	79.97	80.54	81.11	81.67	82.24	82.81	83.38	83.95
19	84.53	86.10	85.67	86.24	86.82	87.39	87.97	88.54	89.12	89.70
	0.0	1.0	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0
20	90.3	96.1	101.9	107.9	113.8	119.9	125.9	132.1	138.2	144.4
30	150.6	156.9	163.2	169.6	176.0	182.4	188.9	195.4	201.9	208.4
40	215.0	221.6	228.3	234.9	241.6	248.4	255.1	261.9	268.7	275.5
50	282.3	289.2	296.1	303.0	309.9	316.9	323.9	330.9	337.9	344.9
60	352.0	359.1	366.2	373.3	380.4	387.6	394.7	401.9	409.1	416.3

APPENDIX 6 : DISTRIBUTION INDEXES

Fruit Squash - Lancashire

Items:	Qu	Co	Ro	RB	Ki	Rs	Su	Vi	Go	We	Sn	Ge	St	OB	PL	MS
Stores :																
Asda	*	*	*	*	*	*	*	*				*		*	*	19.8
Boots			*	*										*	*	1.0
Coop	*		*	*	*	*		*		*				*	*	15.9
Fine Fare	*		*		*	*		*						*	*	3.3
Dee	*	*	*	*	*			*	*	*	*			*	*	1.0
Hillards	*		*	*	*		*	*				*		*	*	0.8
Internl	*		*		*			*	*						*	0.5
KwikSave			*		*	*		*		*	*	*		*		19.4
M&S															*	1.0
Morrisons	*		*	*	*	*		*				*		*	*	3.0
Presto	*		*		*										*	3.0
Safeway	*		*	*	*			*						*	*	2.0
Sainsbury	*		*	*	*	*		*					*	*	*	6.7
Spar	*	*	*	*	*			*						*	*	4.0
Tesco	*		*	*	*	*		*					*	*	*	13.5
Others	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	5.0
Index	79	30	99	73	98	87	26	95	7	41	25	48	25	95	81	100.0

Key : Qu Quosh, Co Corona, Ro Robinsons, RB Robinsons Barley, Ki Kia-Ora, Rs Roses, Su Sunquick, Vi Vimto, Go Gollicrush, We Wells, Sn Sunland, Ge Gee Bee, St St.Clements, OB Other Brands, PL Private Labels, MS Market Share. Stores : Internl International

Fabric Conditioner - London

Items :	Co	Le	So	Ss	SG	OB	PL	MS
Stores :								
Asda	*	*	*					3.0
Boots						*	*	1.0
Coop	*	*	*	*		*	*	7.4
Fine Fare	*	*					*	2.0
Dee	*	*					*	5.0
Internl	*	*	*	*			*	3.0
M&S							*	2.5
Presto	*	*	*				*	2.5
Safeway	*	*	*	*			*	5.6
Sainsbury	*	*	*	*		*	*	40.0
Spar	*	*	*			*	*	1.0
Tesco	*	*	*	*		*	*	16.1
Waitrose	*	*	*	*	*	*	*	6.1
Others	*	*	*	*		*	*	4.8
Index	97	97	90	87	6	68	87	100.0

Key : Co Comfort, Le Lenor, So Softlan, Ss Sosoft, F77 Formula 77,
SG Soft & Gentle, OB Other Brands, PL Private Label, MS Market Share.

Fabric Conditioner - Lancashire

Items :	Co	Le	So	SG	OB	PL	MS
Stores :							
Asda	*	*	*		*		19.8
Boots		*				*	1.0
Coop	*	*	*		*	*	15.9
Fine Fare	*	*				*	3.3
Dee	*	*				*	1.0
Hillards	*	*				*	0.8
Internl	*	*				*	0.5
KwikSave	*	*	*	*	*		19.4
M&S						*	1.0
Morrisons	*	*	*		*	*	3.0
Presto		*				*	3.0
Safeway	*	*	*			*	2.0
Sainsbury	*	*	*			*	6.7
Spar	*	*	*		*	*	4.0
Tesco	*	*	*			*	13.5
Others	*	*	*	*	*	*	5.0
Index	95	99	89	24	67	61	100

Key : Co Comfort, Le Lenor, So Softlan, SG Soft & Gentle,
OB Other Brands, PL Private Label, MS Market Share.

**APPENDIX 7 : DISTRIBUTION INDEX FOR FRUIT SQUASH LONDON FOR A
24 WEEK TIME PERIOD**

Items :	Ro	Ki	RB	OB	Rs	Qu	St	Vi	Su	Go	Cr	We	Sn	PL
Stores :														
Sainsbury	*	*	*	*	*	*	*	*						*
Tesco	*	*	*	*		*		*						*
Coop	*	*	*	*	*	*		*						*
Waitrose	*	*	*	*			*		*					*
Safeway	*	*	*	*	*	*	*	*			*	*		*
Dee	*	*	*	*		*				*		*		*
Others	*	*	*	*	*	*		*	*		*	*	*	*
Internatl	*	*	*	*		*								*
Asda	*	*	*	*	*	*								*
Presto	*	*	*	*	*	*		*						*
M&S														*
Fine Fare	*	*			*									*
Boots	*		*		*									*
Spar	*		*			*		*						*
Index	98	96	96	94	64	91	52	70	11	5	21	17	5	100

Key : Ro Robinsons, Ki Kia-Ora, RB Robinsons Barley, OB Other Brands, Rs Roses,
Qu Quosh, St St.Clements, Vi Vimto, Su Sunland, Go Gollicrush, Cr Corona,
We Wells, Sn Sunquick, PL Private Label.

APPENDIX 8 : 73 TCA PRODUCT FIELDS

Butter	Canned Milk Puddings
Packet Margarine	Canned Pasta Products
Soft Margarine	Baked Beans
Other Yellow Fats	Tinned Soup
Branded Packaged Hard Cheese	Canned Hot Meats (inc. Soya)
Branded Package Soft Cheese	Instant Coffee
Lards and Compounds	Fruit Squash
Cooking Oils	Fruit Juices and Drinks
Yoghurt	Food Drinks
Instant Milk and Non Dairy Creamers	Drinking Chocolate and Cocoa
Evaporated Milk	Packet Tea
Pickles, Chutneys and Relish	Tea Bags
Sauces For Cook and Condiments	Dentifrice
Salad Cream Mayonnaise and Dressings	Toilet Soap
Sauces and Ketchups	Scouring Powder
Powdered Dessert and Custards	Household Cleaners
Meat Extracts	Fabric Conditioners
Instant Mashed Potatoes	Washing Up Products
Ready To Eat Breakfast Cereals	Bleaches and Lavatory Cleaners
Hot Breakfast Cereals	Light Duty Washing Products
Packet Soup	Automatic Washing Products
Complete Dishes	On-Automatic Washing Products
Granulated White Sugars	Kitchen Rolls and Cleaning Cloths
Other Sugars	Toilet Tissues
Canned Milk Puddings	Jams, Curds and Syrups
Marmalade	Digestive Biscuits
Plain and Savoury Rice	Other Sweet and Semi-sweet Biscuits
Savoury Pasta	Plain Biscuits
Jellies	Savoury Biscuits
Cream/Jam Filled Biscuits	Countlines and Mallows
Other Chocolate Biscuits	Flour
Crispbread	Sweet and Savoury Mixes
Dietry Breads	Frozen Vegetables
Wrapped Bread	Frozen Fish Products
Flour	Frozen Meat Products
Frozen Confectionery	
Other Frozen Foods	
Prepared Peas and Beans	

APPENDIX 9 : AN ANALYSIS IF DIRICHLET S PARAMETER VALUES

The following table shows the Dirichlet "S" parameter calculated for the full product field (PF), then for brands only, and finally for private labels only.

Product Field	Region	PF	Brands	PLs
Fruit Squash	London	2.1	1.5	0.7
	Lancs	2.3	1.7	0.5
Fabric Conditioner	London	1.5	1.2	0.7
	Lancs	1.6	1.4	0.5
Baked Beans	London	0.9	1.0	0.5
	Lancs.	1.3	0.9	0.4
Instant Coffee	London	1.2	0.8	0.6
	Lancs.	1.1	0.8	0.4
Washing Up Liquid	London	1.2	1.2	0.5
	Lancs.	1.3	1.0	0.6
Average		1.5	1.2	0.5

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The Buying of Own Labels

by Mark D. Uncles and Katrina Ellis

Brand Names, Brand Loyalty,
Consumer Behaviour, Own-label Goods,
Retailing, USA

Do consumers buy own labels differently from the branded goods of manufacturers? Contrary to some of the beliefs currently held in the trade, own labels are found to be bought much like brands, and loyalty is only slightly above average. Usually, own labels are just one item in a repertoire: consumers will buy other brands, they will buy at other stores, and they will buy the own labels of other stores.

L'achat des marques de distributeurs

Les consommateurs font-ils une discrimination entre les marques des distributeurs ou celles des fabricants? Contrairement à ce que l'on pense actuellement dans le commerce, il a été trouvé qu'ils achetaient les marques de distributeurs à peu près comme les autres marques, et leur loyauté envers elles n'était qu'un peu au-dessus de la moyenne. Les marques de distributeurs ne sont normalement qu'un article du répertoire: les consommateurs achètent d'autres marques, achètent dans d'autres magasins et achètent les marques de d'autres magasins.

Der Kauf von "Own Labels"

Kaufen Verbraucher "Own Labels" von den Herstellern anders als Markenwaren? Im Gegensatz zu emigen der zur Zeit im Handel üblichen Annahmen, werden "Own Labels" ganz ähnlich gekauft wie Markenprodukte, und die Kundentreue liegt nur etwas über dem Durchschnitt. Im allgemeinen sind "Own Labels" nur ein einziger Artikel in einem ganzen Repertoire: Die Verbraucher kaufen auch andere Marken, sie kaufen in anderen Geschäften, und sie kaufen auch die "Own Labels" anderer Geschäfte.

The Buying of Own Labels

The Buying
of Own
Labels

by
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Introduction

Own labels are an established part of retailing today. The reason for this can be seen if we consider the interplay of costs and benefits. When retailers sell goods under their own name, or under an exclusive trade mark, they have the ability to differentiate their stock from other retailers, they might then gain higher gross margins, and they will hope to have more control over product quality, stocks, price, etc [1,2,3].

Retailers also hope to build and sustain store loyalty and develop a competitive edge over other stores and brands [3]. This can be done by charging lower prices, or by offering consumers better value for money without narrowing the range of choice.

For manufacturers, too, there can be advantages in supplying own labels, like securing sizeable market shares, off-loading excess capacity, lowering their distribution costs, and avoiding the expense of national advertising campaigns. But, by the same token, they face the risk of undermining their branded goods and becoming over-reliant on a few buyers [4].

In this article, we examine own labels from the viewpoint of retailers. Specifically, we look at how consumers buy own labels: do they buy them differently from branded items; is increased store loyalty in fact obtained, and do retailers who stock them gain in any way as a result? Factual answers to questions such as these are needed if merchandising and marketing strategies are to be effective.

The trade holds several beliefs about how own labels are bought, but what evidence is there for these? To find out, we report some results for the US ground coffee market, where own labels have a healthy nine per cent market share. Contrary to some of the currently held beliefs, we find that:

- own labels are bought much like leading brands;
- loyalty is, in fact, only slightly above average, and
- own labels are bought along with other brands and other own labels, even when these other items are sold at competing chains.

Although our study is about coffee in the US, the findings tally with some familiar patterns which have been observed for many other products in other countries.

An earlier version of this article was presented at the CESCO Conference in Milan (1987). It is part of an on-going programme of work at the Centre for Marketing and Communication. Studies of buyer behaviour are supported in part by CBS, Colgate Palmolive, General Foods, General Mills, Mars, the Ogilvy Centre and P & G in the US, and by over 30 leading companies in the UK. We also are greatly indebted to MRCA for providing us with raw data.

This means that reliable predictions of how consumers buy own labels can be made using the Dirichlet model [5,6]. This model has been applied to brand buying patterns over many different time periods, different product fields, and different countries. Now we see that the Dirichlet model applies to own labels as well.

In the following sections, we look at some beliefs about own labels, what the evidence shows, how these findings can be generalised, and the merchandising and marketing implications.

What Does the Trade Believe?

Retailers believe that own labels have distinct merits, some of which are listed below. These beliefs come from a variety of surveys and from our own correspondence with retailers.

First among these is that *the impact of own labels is greatest on minor brands* (since the major ones are better able to protect their market shares and resist delisting) [7,8]. Furthermore, it has been suggested that own labels tend to succeed in markets that lack strong brands [3,9]. But even in the trade, many would question this latter point because there are well-known cases where own labels have succeeded in markets with strong brands. For example, Heinz has a major presence in the UK baked bean market, yet own labels are able to secure 35 per cent of this market and, in the London area, their shares are almost equal [10].

Secondly, own labels are seen as *a powerful competitive tool*: they differentiate stock from other chains and help to build and sustain a competitive advantage over other stores [3,7]. At one time, this usually meant that they were "cheap and cheerful" (i.e. inferior substitutes appealing to price-sensitive shoppers). Many have since shifted up-market and now sell on an equal footing with leading brands: the consumer is offered more of the same rather than additional choice. Now competition is more about quality than price. This is seen in the changed emphasis of advertising and in its increased use [9,11,12].

A third point often made by the trade is that *own labels build consumer loyalty to the chain or store* [3,8,9,13,14]. It is argued that they help to establish a distinct corporate identity and set in train a reinforcement process between favoured brands and favoured chains [2,15]. Therefore, in the US, one might think of the "Safeway own-label buyer" as different from buyers at Kroger and A & P, or of differences between Sainsbury and Tesco buyers in the UK [13,16,17,18,19]. In this context, the upgrading of own labels means a better image for the chain.

If such beliefs were in fact true, we would expect them to be confirmed by the way consumers buy these goods.

What Evidence is there for these Beliefs?

In order to examine these points, we studied the ground coffee market in the US, using MRCA [20] data for 1981. This is a suitable product field to study because own labels have meaningful shares in this market (so we avoid problems to do with small samples), there are enough manufacturer brands for us to make useful comparisons, and similar work for this market in the UK means that cross-cultural comparisons can be made.

Our initial findings relate to sales through all the outlets of some major US multiples, such as Kroger and Safeway. Since decisions about own labelling are normally taken by top management, it is appropriate to concentrate on the corporate level. However, similar patterns have been observed at single stores, as discussed in the section on generalisation.

The study is in two parts, looking first at buying within chains and then at buying across competing chains. *Within a chain*, sales of own labels are compared with other brands whose market shares vary. Then we look at the number of sole buyers, and see how much light and heavy buying there is. For multi-brand buyers (i.e. those who buy more than one brand in a given time period), we see whether there are differences in the way own labels and other items in the consumer's repertoire are bought. *Between chains*, we ask whether similar patterns are found throughout the market and how buyers spread their purchases across these chains.

To illustrate these issues, we take the example of Safeway, a major outlet for ground coffee. Here, own labels have an in-store market share of 12 per cent, but the chain's range also includes national brands like Folgers and Maxwell House.

How do the Sales of Own Labels Compare with other Brands?

Sales of a single brand or own label are easily found from the simple sales equation:

$$\text{Sales} = N * b * w * q * p$$

where

- N is the total number of households in the population
- b is the proportion of households buying the brand (i.e. penetration)
- w is the average purchase frequency of these buyers
- q is the average quantity bought
- p is the average price paid per unit.

Of these five quantities, the total number of households and the average price paid per unit are more or less predetermined in the short run. Also, the quantity bought can be considered as fixed because, for most products, people only buy one unit on each purchase occasion. Therefore, the remaining two quantities — b and w — largely determine sales, and our analysis concentrates on these.

Of the 100 million or so households in the US, 1.5 million buy Safeway's own-label ground coffee each year. These buyers account for three million purchases, each having bought it twice on average (Table D).

If we then compare own labels with a brand of similar market share, we find that the components of the sales equation (i.e. b and w) are similar. Maxwell House, with a market share just below that for Safeway own labels, has annual sales of 2.4 million from about one million buyers who buy slightly more than twice a year on average. The figures for a smaller brand like Sanka, with a three per cent market share, are very different: there are fewer buyers and they buy slightly less often.

In fact, it is typical for a small brand to suffer in two ways: it will have fewer

Major Brands	Share of Market at Safeway (%)	Number of Buyers (milhon)	Average Purchase Frequency per Buyer	Sales (milhon)
Any	100	7.5	3.3	24.8
Folgers	25	2.5	2.5	6.3
Own Labels	12	1.5	2.0	3.0
Master Blend	11	1.1	2.4	2.6
Maxwell House	10	1.1	2.2	2.4
Hills Bros	9	0.8	2.7	2.2
Brim	6	0.9	1.6	1.4
Sanka	3	0.6	1.4	0.8
Chock Full O'Nuts	1	0.2	1.0	0.2
Average	10	1.1	2.0	2.4

Table I.
Brand Buying at
Safeway in a Year

buyers, who will buy it less often. For brands, this relationship between the numbers buying and their purchase frequencies is well established. It is the so-called *double jeopardy* effect [19]. Now we see that the way own labels are bought is wholly consistent with this pattern too.

Therefore, people buy own labels in the same way as a brand with a comparable market share.

The same is true about their purchasing of ground coffee in total. The ratio of brand sales to all ground coffee sales in Safeway is roughly the same for own labels as for other brands, as shown in Table II. Buyers of own labels are able to satisfy 48 per cent of their needs from these Safeway brands. Similarly, buyers of the average brand satisfy 43 per cent of their needs from the average brand itself. In terms of purchase occasions, buyers of own labels buy them twice in a year and buy other brands 2.2 times, which gives an annual product field purchasing rate of 4.2 times.

These results (Tables I and II) show that buyers are not as loyal to particular own labels as retailers would like to believe; in fact, people buy them virtually the same way as they do other brands.

Are there any Special Own-label Buyers?

Here we examine sole buyers. These include people who only bought once (who are sole buyers by definition) as well as those who bought more than once, yet who stayed loyal to the one brand or own label.

Roughly 48 per cent of those buying the Safeway own label were sole buyers in a year, which is slightly above the product field average of 38 per cent (it is

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Major Brands	Sales (million)	Product Sales (million)	Share of Requirements (%)
Any	24.8	24.8	100
Folger	6.3	10.0	63
Own Labels	3.0	6.3	48
Master Blend	2.6	5.8	45
Maxwell House	2.4	7.0	34
Hills Bros	2.2	4.2	52
Brim	1.4	4.0	36
Sanka	0.8	2.1	40
Chock Full O'Nuts	0.2	0.9	23
Average	2.4	5.0	43

Table II.
Product Buying at
Safeway in a Year

a lot less than the figure of 53 per cent for buyers of Folgers, but much more than the 24 per cent for Maxwell House buyers) (see Table III). So there are some loyal buyers of own labels, but then there always are *some* loyal buyers, even for brands. This is true in other product fields also [6,19].

Major Brands	Number of Buyers who are Sole Buyers (%)	Average Purchase frequency	Sales from Sole Buyers (million)	Share of Product Sales (%)
Any	100	3.3	24.8	100
Folgers	53	3.0	4.0	40
Own Labels	48	1.5	1.1	17
Master Blend	30	1.1	0.4	7
Maxwell House	24	1.3	0.3	4
Hills Bros	46	1.9	0.7	17
Brim	54	1.6	0.8	20
Sanka	29	1.2	0.2	10
Chock Full O'Nuts	20	1.0	0.04	4
Average	38	1.6	0.7	14

Table III.
Sole Buying at Safeway
in a Year

How Safeway managers regard their sole buyers will depend on whether consumers buy often or not (i.e. how they contribute to sales). Looking again at Table III, we see that in fact only 17 per cent of own-label sales come from this source. The reason why 48 per cent of sole buyers contribute only 17 per cent to sales is that they are very light buyers of the product. They buy just 1.5 times in a year, which contrasts with the average own-label buyer who makes 4.2 purchases of the product at Safeway. This result is not peculiar to buyers at Safeway, a point taken up in the section on generalisation.

The distribution of buying frequencies is relevant too. Typically, there are many once-only buyers and relatively few who buy much more often, as Table IV shows. All the brands sold at Safeway conform to this pattern. In terms of own-label buyers, 65 per cent buy once, whereas only seven per cent make over five purchases in a year. In terms of sales, the distribution shifts towards heavier buyers: 33 per cent of own-label sales are due to the 65 per cent who buy once, whereas 28 per cent of sales are from the seven per cent who buy over five times in a year. This is much in line with the average brand.

Major Brands	Number of Purchases								
	1	2	3	4	5	6	7	8	9+
% of Buyers:									
Own Labels	65	17	7	2	2	2	0	2	3
Average Brand*	66	16	7	3	1	2	2	1	2
% of Volume Sales:									
Own Labels	33	18	10	5	6	7	0	9	12
Average Brand*	31	15	9	6	3	5	5	3	23
*Average across the eight brands listed in Table I.									

Table IV.
Heavy and Light
Buying at Safeway in a
Year

There is an important statistical point to note here. Absolute values depend very much on the length of the time period under study. This is important in any analysis of purchase repertoires, because, by definition, the opportunity to buy (and therefore to switch brands) is lower in shorter periods like a week than in longer time periods. This is one reason why we concentrate on annual figures; after a year we stand a better chance of observing the buyer's full repertoire.

How do Customers Spread their Purchases across Brands?

Despite there being some sole buyers, it is usually the case that most customers buy other brands as well. As we saw in the previous section, the sales importance of these other purchases is considerable. The buying of other brands in this way is called *duplication* and buyers who spread their purchases across brands are called *multi-brand buyers*.

More than half the buyers of Safeway own labels also buy other brands of ground coffee in a year. Table V shows exactly which other brands are bought and this enables us to see how own labels compete with specific brands.

Reading across the first row of Table V, about 19 per cent of Folgers buyers also buy Safeway own labels, 13 per cent Master Blend, 11 per cent Maxwell House and so on. A similar pattern emerges for own labels in the second row. This gradual fall in the number of duplicate buyers as one reads across the row is matched by a steady decline in market shares.

Major Brands Safeway buyers of:	Who also bought at Safeway:							
	F	OL	MB	MH	HB	B	S	C
Folgers	-	19	13	11	8	3	4	4
Own Labels	30	-	13	11	7	9	2	4
Master Blend	30	18	-	39	6	9	6	6
Maxwell House	24	15	38	-	9	12	6	0
Hills Bros	25	13	8	13	-	13	8	0
Brim	8	15	12	15	8	-	15	0
Sanka	18	6	12	12	12	24	-	0
Chock Full O'Nuts	20	13	13	0	0	0	0	-
Average Duplication	22	14	16	14	7	10	6	2
Predicted Duplication	26	16	12	12	9	9	6	2
Percent Buying	33	20	15	15	11	11	7	2

Table V.
Multi-brand Buying at
Safeway in a Year

It is only when market shares are low, say one per cent for Chock Full O'Nuts, that oddities appear. In the case of Chock Full O'Nuts, oddities arise because of small sample sizes and because this brand has an even more limited retail distribution than own labels, so there is little opportunity to buy it.

In practice, there are few oddities. Generally, buyers of one brand also buy competing brands in proportion to the penetration of these other brands. So own labels are bought more by buyers of brand leaders than by buyers of small brands. Similarly, own-label buyers are more likely to buy the brand leader than a smaller brand. From this pattern, we can infer that there is no clear brand segmentation in the market (i.e. no special tendency for one brand to be duplicated with another more or less than what one would expect given their penetration levels).

These regularities are so strong that they can be replicated using a simple coefficient (i.e. average duplication divided by average penetration). If we then multiply brand penetrations by this coefficient we are able to predict levels of duplication. The predictions for Safeway buyers are shown in the penultimate line of Table V.

Sales are influenced far more by the varying number of multi-brand buyers (as

shown in Table V) than by the fairly constant purchase frequencies which are typical among duplicate buyers. Thus, if an own-label buyer obtains another brand at all, he/she will do so twice in a year; the Folgers buyer will do so almost twice; likewise the Master Blend buyer, and so forth. Such patterns — with varying numbers buying and constant purchase frequencies — have been identified for many other product fields [6].

How do Customers Spread their Purchases across Chains?

Retailers see own labels as one way to differentiate their own stock from that of competitors, and they hope that somehow this will increase store loyalty. If this were true, we would expect to see consumers engaging in selective buying. Thus, Safeway own-label buyers would behave differently from those at Kroger, and shoppers at each chain would rarely buy from the other. But when *all* retailers strive for this, we must be clear about who gains. They cannot all differentiate their stock and simultaneously raise the number of loyal customers — if one retailer does this it will be at the expense of another.

The alternative proposition is that consumers treat own labels just like any other brand, regardless of where they shop. So a consumer is equally likely to buy Safeway own labels as he/she is to buy those sold at Kroger (assuming their market shares are similar).

In this section we look at sole buying (an indicator of loyalty) and duplication across chains (an indicator of divided loyalty) to see what, in fact, occurs. The number of sole buyers and their purchase frequencies are almost constant across chains; so, too, is their contribution to ground coffee sales at about 25 per cent of all purchases. For instance, of own-label buyers at Safeway, 48 per cent are sole buyers. The proportion at Kroger is slightly less, whereas, at A&P, it is somewhat more. And at all chains, these sole buyers buy less frequently than the average customer; just 1.6 times, as against an average of twice each year.

To see where the other purchases of the product are made, we must look at duplication across stores. Normally, this is high when market shares are high. Thus own-label buyers at Safeway are more likely to buy Kroger own labels than they are to buy A&P's, and for no other reason than Kroger serves a larger market (both in terms of absolute volume and geographical coverage). In Table VI, for instance, 13 per cent of those buying Safeway own labels also buy Kroger's, whereas only seven per cent buy A&P's.

In general, all the chains which sell own-label ground coffee have the number of sole buyers and the amount of duplicate buying that we would expect from knowing their penetrations. In this sense, patterns of loyalty for own labels are similar to those for brands of similar size [19].

The few oddities that exist have little to do with chains as such — they largely arise from trading area effects (i.e. some chains operate in exactly the same geographical areas, others overlap much less). For example, Table VI shows that nine per cent of own-label buyers at Safeway also buy them from Lucky. Given the latter's penetration of four per cent this is surprisingly high. (In fact it is higher than the duplication with A&P, a chain which has a penetration of 14 per cent.)

The overlap of trade areas in California offers a simple reason for this high level of duplication between Safeway and Lucky [21,22].

Chains	Who also bought the own label at:								
	Major groupings				Named chains				
Own-label Buyers at:	G	MM	W	C	K	AP	WD	S	L
Major Groupings									
Grocers	-	20	9	4	25	12	9	8	3
Misc Multiples	44	-	4	6	7	13	8	4	0
Wholesalers	42	8	-	2	32	4	0	6	8
Convenience	53	32	5	-	32	16	11	0	5
Named Chains									
Kroger	54	7	15	6	-	4	3	6	2
A&P	44	22	3	5	6	-	3	5	2
Winn Dixie	48	19	0	5	7	5	-	0	0
Safeway	39	9	7	0	13	7	0	-	9
Lucky	38	0	25	6	13	6	0	25	-
Average Duplication									
	45	15	9	4	17	8	4	7	4
Predicted Duplication									
	39	18	8	3	18	10	7	7	3
Percent Buying									
	53	24	11	4	24	14	10	10	4

Table VI.
Multi-chain Buying of
Own Labels in a Year

So the evidence on how people spread their purchases across chains is mixed: there are many sole buyers at individual chains, but they are light buyers and not that important in terms of sales. Heavier buyers, who make the largest contribution to sales, have more opportunity to shop elsewhere, and their patronage of other stores confirms this.

Can the Findings be Generalised?

Own labels are bought just like any other brand with a similar market share. Some buyers remain loyal to one chain and one own label, but most consumers will buy elsewhere. This is so within and between chains. It is usual for consumers to select from a repertoire of brands and stores.

What *does* vary from one chain to another is sales levels (and therefore in-store market shares). Own labels account for almost 40 per cent of ground coffee sales at Kroger, a figure that falls to nine per cent at Lucky. Even the proportion

at Lucky is high compared with what happens at local multiples and independent grocers (four per cent and five per cent respectively). Own-label sales, then, are heavily concentrated in national and regional chains where they are bought as if they were a leading brand.

Would these conclusions be different if our scale of analysis was a single metropolitan area, or if British data or another product field was examined instead? Would the sales relationships differ if we studied longer or shorter time periods? The results are in this sense robust. We can make this claim for two reasons: a rigorous model (the Dirichlet) bears out what we have found from observation, and these results are consistent with what has been found in other empirical studies.

Major Brands	Number of Buyers (million)		Average Purchase Frequency per Buyer		Share of Requirements (%)	
	O	D	O	D	O	D
Any	7.5	7.5	3.3	3.3	100	100
Folgers	2.5	2.9	2.5	2.2	65	55
Own Labels	1.5	1.5	2.0	2.0	48	48
Master Blend	1.1	1.3	2.4	2.0	45	47
Maxwell House	1.1	1.3	2.2	2.0	34	47
Hills Bros	0.8	1.1	2.7	2.0	52	46
Brim	0.9	0.7	1.6	1.9	36	45
Sanka	0.6	0.4	1.4	1.9	40	44
Chock Full O'Nuts	0.2	0.1	1.0	1.9	23	42
Average	1.1	1.2	2.0	2.0	43	47
O Observed values D Dirichlet predictions.						

Table VII.
Predictions of Buyer
Behaviour at Safeway
in a Year

The Dirichlet is a stochastic model of buyer behaviour that has been applied with much success in the packaged grocery goods sector. Detailed accounts of the theory are provided by Goodhardt *et al.* [5] and Ehrenberg [6]. Here, we need only note that in order to make predictions, just three pieces of information are required: the distribution of purchases for the whole product field, each brand's share of the market, and a measure of the diversity of brand choice (such as the average number of brands bought). With a knowledge of just these few facts, we can predict all the standard measures of buyer behaviour, and then show how buying patterns for own labels are predictably similar to those for brands.

For example, in Table VII, penetrations, average purchase frequencies and shares of requirements are closely predicted by the model. There are 2.5 million buyers of Folgers in a year and 2.9 predicted; there are 1.5 million own-label buyers and

our prediction exactly matches this, and so forth for other brands sold at Safeway.

Much the same can be said for sole buyers, for their average purchase frequencies, and for their sales effects, as shown in Table VIII. The fit is not perfect and there are a few oddities, but these stand out from the theoretical norms simply because the overall fit is so close. Thus, the observed number of own-label sole buyers (48 per cent) is noticeably higher than what we would expect from the theoretical norm (39 per cent). Figures for Maxwell House are the other way round: the number of sole buyers is over-predicted.

Major Brands	Number of Buyers who are Sole Buyers (%)		Average Purchase Frequency per Sole Buyer		Sales from Sole Buyers (million)	
	O	D	O	D	O	D
Any	100	100	3.3	3.3	24.8	24.8
Folgers	53	46	3.0	1.9	4.0	2.5
Own Labels	48	39	1.5	1.7	1.1	1.0
Master Blend	30	39	1.1	1.7	0.4	0.9
Maxwell House	24	39	1.3	1.7	0.3	0.9
Hills Bros	46	38	1.9	1.7	0.7	0.7
Brim	54	37	1.6	1.6	0.8	0.4
Sanka	29	36	1.2	1.6	0.2	0.2
Chock Full O'Nuts	20	35	1.0	1.6	0.04	0.06
Average	38	39	1.6	1.7	0.7	0.8

O Observed values
D Dirichlet predictions.

Table VIII.
Predictions of Sole
Buying at Safeway in a
Year

The distribution of light and heavy buyers is also closely predicted from theory. The figures in Table IX show once again that consumers treat own labels much like other brands.

In several studies of the behaviour of British consumers, both nationally and within single cities, similar patterns have been found [23,24,14]. These reports include a variety of product fields where own labels have a sizeable share of the market, such as margarine, baked beans and instant coffee. Scanner panel data for several US cities provide further evidence, not only within chains but also within stores. The same basic message comes across from all these studies: the buying of own labels is usually very similar to the way comparably sized brands are bought, and these buying patterns are sufficiently general that they can be predicted.

Major Brands	Number of Purchases									
		1	2	3	4	5	6	7	8	9+
% of Buyers:										
Own Labels	O	65	17	7	2	2	2	0	2	3
	D	65	17	7	4	2	1	1	1	2
Average Brand*	O	66	16	7	3	1	2	2	1	2
	D	65	17	7	4	2	1	1	1	2
% of Volume Sales:										
Own Labels	O	33	18	10	5	6	7	0	9	12
	D	33	17	10	7	5	4	4	3	17
Average Brand*	O	31	15	9	6	3	5	5	3	23
	D	32	17	10	7	5	4	4	3	18
* Average across the eight brands listed in Table I.										
O Observed values										
D Dirichlet predictions.										

Table IX.
Predictions of Heavy
and Light Buying at
Safeway in a Year

What are the Implications?

To make good marketing decisions, reasonably accurate and usable information is needed. Yet, all too often, only partial information is to hand, and this may lead to the formulation of inappropriate strategies. For instance, retailers assume that the consumer buys own labels selectively — but this is not supported by the evidence. In fact, our research casts doubt on several strategic uses of own labels: that they play a significant role in building and sustaining store loyalty, that they differentiate stock in such a way that consumers actually change their behaviour, and that they compete mostly with minor brands.

Instead, what we find is that consumers appear to treat own labels just like any other brand: there happen to be some loyal buyers, but most people have a repertoire. They will buy other brands; they will buy at other chains and they will buy the own labels of other chains. There is so little difference in the actual buying of manufacturer brands and own labels, we wonder whether consumers simply see them as alternative brands.

Another implication of this study is that the performance of own labels can be judged against norms. For example, given that 36 per cent of own-label sales at Safeway come from those who are wholly loyal to this item, should this be seen as 'only' 36 per cent or 'as many as' 36 per cent or is it 'just about right'? The absolute figure has little meaning without comparable information, such as the theoretical norms. If fewer people than expected are loyal, this can be identified, and positive action, such as an in-store promotion, can be taken.

This study does not imply that an own-label strategy is of no benefit to the retailer. On the contrary, there may be many operational and cost-related benefits; for example, more control over price, quality, stock assortment and shelf allocation,

coupled with higher gross margins which should feed through into higher profits. These potential benefits, however, must be set against the costs and risks that head office faces when it takes on the task of selling own labels.

In this study we have concentrated on finding out how people buy brands and own labels before attempting to discover why they do so. This is by no means the full story, and attitude surveys and consumer experiments are in progress to gain a deeper knowledge of this process. Altogether, this work holds out the prospect of providing retailers with some factual evidence on which to base their future marketing strategies for own labels.

References

1. Rothe, J.T. and Lamont, L.M., "Purchase Behavior and Brand Choice Determinants for National and Private Brand Major Appliances", *Journal of Retailing*, Vol. 49, Fall, 1973, pp. 19-33.
2. McGoldrick, P.J., "Grocery Generics — An Extension of the Private Label Concept", *European Journal of Marketing*, Vol. 18, 1984, pp. 5-24.
3. Simmons, M. and Meredith, W., "Own Labels Profile and Purpose", *Journal of the Market Research Society*, Vol. 26, 1984, pp. 3-27.
4. Morris, D., "The Strategy of Own Brands", *European Journal of Marketing*, Vol. 13, 1979, pp. 59-78.
5. Goodhardt, G.J., Ehrenberg, A.S.C. and Chatfield, C., "The Dirichlet: A Comprehensive Model of Buyer Behaviour", *Journal of the Royal Statistical Society A*, Vol. 147, 1984, pp. 621-55.
6. Ehrenberg, A.S.C., *Repeat-Buying: Facts, Theory and Applications*, new ed., Griffin, London; OUP, New York, 1988.
7. Frank, R.E. and Boyd, H.W., "Are Private-brand-prone Grocery Customers Really Different?", *Journal of Advertising Research*, Vol. 5, 1965, pp. 27-35.
8. "The Development of Own Brands in the Grocery Market", *Retail Business*, Vol. 166, December 1971, pp. 27-35.
9. Euromonitor, *The Own Brands Report*, available from Euromonitor Publications Ltd, 87-88 Turnmill St, London EC1M 5QU, 1984.
10. "Market Analysis Package for Baked Beans", *TCA Report*, available from Audits of Great Britain Ltd, West Gate, London W5 1UA, 1985.
11. IPA, *The Growth of Retailer Power*, available from the Institute of Practitioners in Advertising, 44 Belgrave Sq., London SW1X 8QS, 1980.
12. Euromonitor, *The Own Brands Report*, available from Euromonitor Publications Ltd., 1986.
13. Cunningham, R.M., "Consumer Loyalty to Store and Brand", *Harvard Business Review*, Vol. 39, November-December 1961, pp. 127-37.
14. Wrigley N. and Dunn, R., "Stochastic Panel-data Models of Urban Shopping Behaviour: 3. The Interaction of Store Choice and Brand Choice", *Environment & Planning A*, Vol. 16, 1984, pp. 1221-36.
15. Dole, J., "Dutch Own-labels Jostle big Brands", *Focus*, April 1987, pp. 24-5.
16. Rao, T.R., "Are Some Consumers More Prone to Purchase Private Brands?", *Journal of Marketing Research*, Vol. 6, 1969, pp. 447-450.
17. Charlton, P., "A Review of Shop Loyalty", *Journal of the Market Research Society*, Vol. 15, 1973, pp. 25-41.
18. Stoessl, S., "Is the Real Consumer Brand of the Future the Retailer: Is Shop Loyalty Taking over from Brand Loyalty?", *Admap*, November 1979, pp. 587-90.

19. Ellis, K., *An Investigation of Private Label Purchase Behaviour in the Packaged Grocery Market*, PhD thesis, London Business School, 1988.
20. MRCA: Panel data for the first 48 weeks of 1981 from the Market Research Corporation of America, Northbrook, Illinois.
21. Uncles, M.D. and Ehrenberg, A.S.C., "Patterns of Store Choice: New Evidence from the USA", in Wrigley, N. (Ed.), *Store Choice, Store Location and Market Analysis*, Routledge, London, 1988, pp. 272-89.
22. Uncles, M.D. and Ehrenberg, A.S.C., "The Buying of Ground Coffee", available from CMAc, London Business School, 1988.
23. Aske Research, *The Structure of the Biscuit Market*, contact CMAc, London Business School, Sussex Place, London NW1 4SA, 1976.
24. Kau, A.K. and Ehrenberg, A.S.C., "Patterns of Store Choice", *Journal of Marketing Research*, Vol. 21, 1984, pp. 399-409.

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Own labels: beliefs and reality

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Introduction

Own labels are an established part of retailing today. When retailers sell goods under their own name, or when they use an exclusive trademark, they gain direct control over product quality, and usually they secure higher margins. They also hope that by having own labels 'their buyers' will be more loyal and that this will give them a competitive edge over other stores.

A manufacturer who agrees to supply own labels can gain too: by selling large volumes, by lowering the cost of distribution, and by avoiding the expense of national advertising campaigns. But, by the same token, having to rely on a few key accounts is not without its dangers, and it might be feared that the long-term strength of leading brands is undermined.

For consumers the possible benefits are likely to come in the form of lower prices, guarantees of quality and better value-for-money.

Overall, the interplay of costs and benefits for different groups in the distribution chain is complex. This paper is not an attempt to unravel all the complexities, instead the issues are largely looked at from the retailer's perspective. Specifically, we see how consumers buy own labels, and whether increased store loyalty is in fact obtained. For instance, do consumers buy own labels differently from branded items, and do retailers who stock them gain in any way as a result? Such questions ought to be answered if merchandising and marketing strategies are to be effective.

Several popular beliefs are held about how own labels are bought, and it is around these that our empirical work is arranged. These beliefs are outlined in the next section, and in the third section we look at the degree to which these tally with what is observed in practice. The issue of whether our findings generalize is taken up in the next section and we conclude in the last section with a discussion of the implications.

The empirical context for this study is the US ground coffee market, a market where own labels have a healthy 9 per cent share. We will be saying, contrary to some of the beliefs currently held in the trade, that own labels are bought much like leading brands, and loyalty is only slightly higher than average. Usually they are just one item in a repertoire of brands bought by the consumer, and they are even bought along with own brands sold at competing chains. Although our study is about coffee, *this product is simply used as an illustration*. The findings generalize, to the extent that from a well-proven model of consumer behaviour reliable predictions can be made of own-label buying. Nor is this result confined to the US, it also applies in the UK, and for chains and individual stores, and across many different product fields.

What does the trade believe?

Retailers believe that own labels have several distinct merits. First among these is that they are a *powerful competitive tool* they differentiate stock from other chains, and help to build and sustain a competitive advantage over other stores. At one time this invariably meant that own labels were 'cheap and cheerful' (that is, inferior substitutes appealing to price-sensitive shoppers). Most have now shifted up market and, ironically perhaps, far from differentiating the stock by price, many now sell on an equal footing with leading brands: the consumer is offered more choice at the same price (IPA 1980; Euromonitor 1984, 1986).

Today competition is usually based on quality, leaving generics to fight on price alone – although it is debatable whether the differences between own labels and generics are clearly perceived by consumers (McGoldrick 1984; Chernatony 1988). Managers will tell you that much of their success lies in 'the good value and range' of their own labels, and that 'increasing the proportion of own labels and enhancing product quality has been crucial to improved performance'.

A second point frequently made by the trade is that *own labels build consumer loyalty to the chain or store*. Own labels, it is argued, help to establish a distinct corporate identity, and they help to reinforce

buying at favoured chains. Therefore, one thinks of the 'Safeway own-label buyer', who is different from a buyer at Kroger, who is different again from an A & P buyer, or differences between Tesco and Sainsbury buyers in the UK (Cunningham 1961; Rao 1969; Charlton 1973; Stoessl 1979; Simmons and Meredith 1984).

Retailers often say how the growth of own labels has 'given their stores a distinctive personality and built an image'. This can be a winning combination, especially when their chain has a growing reputation for innovation, product quality, and value-for-money. Seen in this light, the upgrading of own labels means a better image for the chain – though if all major chains follow suit it is hard to see who makes an exceptional gain – there can be no rich prizes for everyone.

Sometimes it is argued that the *impact of own labels is greatest on minor brands*, if only because minor brands are less able to protect their market shares and resist delisting. Therefore own labels will succeed where there are few strong brands. But even in the trade there is much uncertainty about this, and there are some well-known cases where own labels have succeeded in markets with strong brands (Euromonitor 1984).

What evidence is there for these beliefs?

The extent to which these popular beliefs are true will be apparent from the way consumers buy their goods, as revealed by the level of sales, sole buying, light and heavy purchasing, and store and brand loyalty. Surprisingly, little hard evidence of this nature has been published hitherto. In order to rectify this situation we have studied what happens in a diverse group of product fields.

For illustrative purposes we report on the ground coffee market in the United States, using MRCA data for 1981 (a more detailed account is to be found in Uncles and Ellis 1989). Our initial findings relate to sales through major multiples, such as Safeway and Kroger. Since decisions about own labelling are normally taken by central buyers and merchandisers, we feel justified in concentrating on the corporate level. Later, however, we refer to similar patterns which have been observed at single stores.

The study falls into two parts, dealing in turn with in-store and between-store buying or, in managerial terms, merchandising and competition respectively. First, within a chain, sales of own labels are compared with both major and minor brands. Then we ask whether there are any special own-label buyers and, if so, is their purchasing heavy or light? And where several brands are bought, what differences are there between own labels and other items in the consumer's

repertoire? Second, we consider what happens between chains: are similar patterns found at every chain, and how do people buy across different chains?

How do sales of own labels compare with other brands?

Consider the case of Safeway: as a major outlet for ground coffee Safeway sells leading brands like Maxwell House and some speciality brands such as Sanka, none the less 12 per cent of its sales come from own labels. Of the 100 million households in the United States, 1.5 million buy Safeway's ground coffee own labels each year, and on average they do so about twice. Total sales amount to 3 million items.

If own labels are compared with a brand having a similar market share we find that the components of the sales equation are fairly similar. For instance, Maxwell House, with a market share just below Safeway's own labels, has annual sales of 2.5 million from about 1 million buyers who buy just over twice on average (Table 15.1). This contrast with the figures for a much smaller brand like Sanka. In short, the way brands are bought largely depends on their market shares, and own labels are not unusual in this respect.

To a degree this is also true of ground coffee purchasing in total. Those who buy own labels make 6.3 million purchases of ground coffee altogether, which means that 52 per cent of their needs are met by brands *other than* own labels. This is similar to what is found elsewhere: across leading brands some 56 per cent of requirements are met by brands *other than* the one under study. Buyers of own labels just like buyers of other brands will select from a repertoire. The final choice of what goes into each repertoire being influenced by qualities of the brand itself (taste, price, value-for-money, etc.) and by the needs of users (drinking coffee to quench thirst, when waking in the morning, when entertaining, etc.). What all this means is that

Table 15.1 Brand buying at Safeway in a year

Brands	Market share at Safeway	Penetration of the brand	Average purchase frequency per buyer	Sales of the brand	Sales of all ground coffee
	(%)	(mill)		(mill)	(mill)
Selected brands					
Own labels	12	1.5	2.0	3.0	6.3
Maxwell House	10	1.1	2.2	2.5	7.0
Sanka	3	0.6	1.4	0.8	2.1
Average (8 brands)	11	1.3	2.0	2.6	6.0

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buyers are not as loyal to particular own labels as retailers would like to believe.

Are there any special own-label buyers?

Roughly 48 per cent of those buying own labels in a year are sole buyers (that is, they buy this item alone). This is above the general level of sole buying and is much higher than for Maxwell House and Sanka (Table 15.2). It certainly looks as if there are some special own-label buyers; but how does this square with the fact that many other buyers choose to select from a repertoire? Sales figures hold the key. Sole buyers buy own labels (and the product) less often than other customers just 1.5 times a year. This contrasts with the average customer who makes two brand purchases and over four product purchases. Thus, of all ground coffee sales from own-label buyers, only 17 per cent accrue from sole buyers. Later we show that within chains this is a common pattern, and it would be wrong to think of shoppers at Safeway as being unusually fickle.

Therefore, how often purchases are made is crucial. The distribution of buying frequencies describes another aspect of this: typically there are many once-only buyers and relatively few heavy buyers. All the brands sold at Safeway conform to this pattern. Of own-label buyers, 65 per cent buy once, 17 per cent buy twice, and only 7 per cent make over five purchases. In terms of sales the distribution shifts towards heavier buying: 33 per cent of sales are from those who buy once, 18 per cent from those buying twice, and 28 per cent from those who buy more than five times.

When interpreting these figures it should be kept in mind that absolute values depend on the length of period under study. Almost by definition the opportunity to buy is low in short periods, giving rise to apparent loyalty and once-only buying (this is one reason why we

Table 15.2 Sole buying of brands of Safeway in a year

Brands	Sole buyers as a % of all buyers	Average purchase frequency per sole buyer	Sales from sole buyers (mill.)	Share of ground coffee sales by brand (%)
Selected brands	(%)		(mill.)	(%)
Own labels	48	1.5	1.1	17
Maxwell House	24	1.3	0.3	5
Sanka	29	1.2	0.2	10
Average (8 brands)	39	1.9	1.0	17

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concentrate on annual figures). Similarly, brands with small market shares are bought less often by those who buy them at all, so light buying dominates the picture. For example, even over a year Sanka derives 65 per cent of its sales from once-only buyers, whereas Maxwell House gets only 29 per cent of sales in this way. In this respect the distribution of purchases for own labels is true to form given the levels of market share.

How do customers spread their purchases across brands?

Despite the existence of sole buyers, many customers buy other brands as well (that is, they duplicate buy) and, as we have seen, the sales importance of these other purchases is considerable. More than half Safeway's own-label buyers obtain other brands of ground coffee as well. About 30 per cent of these buy Folgers, 11 per cent buy Maxwell House, and just 2 per cent buy Sanka; these differences being correlated with relative levels of market share and penetration (Table 15.3).

Buyers of Maxwell House show a similar link between penetration and duplication. It is only when market shares are low, say 6 per cent for Sanka, that oddities emerge and these largely arise because of small sample sizes and limited retail distribution.

Rates of multi-brand buying hardly vary: if an own-label buyer obtains another brand at all, s/he will do so twice in a year, the Maxwell House buyer will do so 2.3 times, and the Sanka buyer 1.4 times.

Overall, these patterns are so strong that we can replicate the

Table 15.3 Multi-brand buying at Safeway in a year

Brands	Who also bought at Safeway.						
	F	OL	MB	MH	HB	B	S C
Safeway buyers of:							
Folgers (F)	19	13	11	8	3	4	4
Own labels (OL)	30	18	13	11	7	9	2
Master Blend (MB)	30	18	39	6	9	6	4
Maxwell House (MH)	24	15	38	—	9	12	6
Hills Bros (HB)	25	13	8	13	13	8	0
Brim (B)	8	15	12	15	8	15	0
Sanka (S)	18	6	12	12	12	24	0
Chock Full O'Nuts (C)	20	13	13	0	0	0	—
Average duplication	22	14	16	14	7	10	6
Predicted duplication	26	16	12	12	9	9	6
Per cent buying	33	20	15	15	11	11	7
							2

duplication effects using a simple coefficient (that is, average duplication divided by average penetration). What we find, to a first order of approximation, is that buyers obtain competing brands in proportion to the average penetrations. An implication of this is that there is no clear brand segmentation of the market, though there may be 'needs segmentation' based on the variety of ways coffee is drunk.

How do customers spread their purchases across chains?

A popular belief is that, by offering own labels, store loyalty will rise somehow; if this was true we would expect to see consumers engaging in selective buying. Thus, Safeway own-label buyers would behave differently from those at Kroger, and members of each group would rarely buy from competing chains. The alternative proposition is that consumers treat own labels just like any other brand, regardless of where they shop. We look at sole buying within different chains and duplication across chains to see which proposition is most plausible.

The number of own-label sole buyers, and their purchase frequencies, are almost constant from chain to chain, so too is their contribution to sales at about 25 per cent of all purchases. Earlier we saw how the 48 per cent of own-label buyers at Safeway, who buy there and nowhere else, are light buyers of both that specific item and ground coffee in general. What we now find is that despite some variation between stores (for instance, the proportion at Kroger is slightly less, whereas at A & P it is somewhat more), sole buyers are always somewhat less frequent buyers than the average customer – they buy just 1.6 times as against twice on average.

The remaining buyers are prepared to shop around; they try other brands and patronize other chains. Exactly where else goods are bought is shown by the duplication table (Table 15.4). Normally duplication is high when market shares are high; thus own-label buyers at Safeway are more likely to buy Kroger own-labels than they are to buy A & P's, and for no other reason than Kroger serves a larger market (both in terms of absolute volume and geographical coverage). For instance, we find that 13 per cent of people who buy Safeway own labels also buy Kroger's, whereas only 7 per cent buy A & P's.

The few anomalies that exist seem to be associated with chains whose trading areas are very similar (that is, these chains operate in exactly the same geographical areas, whereas the trading areas of other chains overlap much less) (see Table 15.4). For instance, 9 per cent of own-label buyers at Safeway also buy own labels from Lucky, and given Lucky's market share this is surprisingly high. However, the opportunity for buying at both chains is very high in California

Table 15.4 Multi-chain buying of own labels in a year

Chains	Who also bought the own label at									
	Major groupings			Named chains						
	G	M	W	C	K	AP	W/D	S	L	
<i>Own-label buyers at:</i>										
<i>Major groupings</i>										
Grocers (G)	—	20	9	4	4	25	12	9	8	3
Misc Multiples (M/M)	44	—	4	6	7	7	13	8	4	0
Wholesalers (W)	42	8	8	2	2	32	4	0	6	8
Convenience (C)	53	32	5	—	—	32	16	11	0	5
<i>Named chains</i>										
Kroger (K)	54	7	15	6	6	4	3	6	2	2
A & P (AP)	44	22	3	5	7	6	3	5	2	0
Winn Dixie (W/D)	48	19	0	5	7	5	7	0	0	0
Safeway (S)	39	9	7	0	13	7	0	0	9	9
Lucky (L)	38	0	25	6	13	6	0	25	—	—
<i>Average duplication</i>										
Predicted duplication	45	15	9	4	4	17	8	4	7	4
Per cent buying	39	18	8	3	3	18	10	7	7	3
	53	24	11	4	4	24	14	10	10	4

where their trade areas coincide (Uncles and Ehrenberg 1988). The important point is that the few differences which do exist have little to do with brands as such, and are largely due to trading area effects.

The evidence, then, is mixed: although there are sole buyers at individual chains, they are light buyers, and are not so important in terms of sales. By contrast, heavier buyers make a larger contribution to sales, but they have more opportunity to buy elsewhere; in fact, 60 per cent choose to shop at competitors as well.

Do our findings generalize?

The manager of another chain might well accept these findings, but he may doubt whether they describe his own customers (it is not uncommon to be told: that may be true for others, but my business is different). To the extent that we can see how far the findings apply at other chains the issue is largely empirical.

The market share of own labels varies from one chain to another. At Kroger they account for almost 40 per cent of ground coffee sales, whereas at Lucky the figure is no more than 9 per cent. Even the proportion at Lucky is high when compared with local multiples and independent grocers: sales at these are 4 per cent and 5 per cent respectively. With this degree of concentration in national chains it

might be thought that the structure of buying would be very different from that at, say, independent grocers.

What happens is that while the absolute figures do indeed vary, the underlying structure does not. The composition of sales, the proportion who are sole buyers, the incidence of duplicate buying – all these aspects of buyer behaviour tally with what we would expect from knowing the market shares. Nor are own labels strikingly different from other brands; patterns of loyalty, duplicate buying, and so forth, are on a par with what has been observed for manufacturers' brands with similar market shares. Moreover, like buyers in general, some will remain loyal to a specific own label, but most buy from a repertoire of brands, including own labels sold elsewhere.

A rigorous model, giving reliable predictions, bears out what has been found by observation. To fit this model all we need to know is the distribution of purchases in the whole product field, the average number of brands bought, and each brand's share of the market. With a knowledge of just these few facts – for a base period – we can predict all the standard measures of behaviour, showing for example how the buying of own labels is predictably similar to the buying of brands of a comparable size.

Detailed accounts of the theory, based on the NBD-Dirichlet model, are given elsewhere (Goodhardt *et al.* 1984; Ehrenberg 1988), and the results presented here are only meant to be indicative. None the less, from even the most basic predictions, it is clear from Table 15.5 that the goodness of fit is reasonable. The few anomalies that exist stand out from the theoretical norms (for instance, the observed excess of sole buyers compared to the theoretical percentage) – this also shows how the model can have a useful diagnostic role.

The distribution of purchases (that is, light and heavy buying) is also closely predicted from theory, and again consumers appear to treat own labels much like other brands (Table 15.6).

Even if the retailer is prepared to accept this, he might still doubt whether these conclusions alter when the scale of analysis shifts to a single metropolitan area, or if British data are examined instead, or if sales relationships are studied over longer or shorter time periods.

All these conditions have been studied. For instance, national and single-city studies of British consumers confirm what has now been found in the United States (Aske Research 1976; Kau and Ehrenberg 1984; Wrigley and Dunn 1984). These reports cover a variety of products where own labels have a sizeable share of the market, such as margarine, baked beans, and instant coffee. Recently a more systematic study, concentrating on own labels, has been undertaken (Ellis 1989).

Table 15.5 Predictions of buyer behaviour at Sateway in a year

Major brands	Number of buyers		Average purchase per buyer		Number of sole buyers		Average purchase per sole buyer	
	O	D	O	D	O	D	O	D
Any	7.5	7.5	3.3	3.3	100	100	3.3	3.3
	(mill.)				(%)			
Folgers	2.5	2.9	2.5	2.2	53	46	3.0	1.9
Own labels	1.5	1.5	2.0	2.0	48	39	1.5	1.7
Master Blend	1.1	1.3	2.4	2.0	30	39	1.1	1.7
Maxwell House	1.1	1.3	2.2	2.0	24	39	1.3	1.7
Hills Bros	0.8	1.1	2.7	2.0	46	38	1.9	1.7
Brim	0.9	0.7	1.6	1.9	54	37	1.6	1.6
Sanka	0.6	0.4	1.4	1.9	29	36	1.2	1.6
Chock Full O'Nuts	0.2	0.1	1.0	1.9	20	35	1.0	1.6
Average	1.1	1.2	2.0	2.0	38	39	1.6	1.7

Notes:
O = Observed values.
D = Dirichlet predictions.

Table 15.6 Predictions of heavy and light buying at Sateway in a year

Brands	Number of purchases									
	1	2	3	4	5	6	7	8	9+	
% of buyers: Own labels	O	65	17	7	2	2	2	0	2	3
	D	65	17	7	4	2	1	1	1	2
Average (8 brands)	O	66	16	7	3	1	2	2	1	2
	D	65	17	7	4	2	1	1	1	2
% of volume sales: Own labels	O	33	18	10	5	6	7	0	9	12
	D	33	17	10	7	5	4	4	3	17
Average (8 brands)	O	31	15	9	6	3	5	5	3	23
	D	32	17	10	7	5	4	4	3	18

Notes:
O = Observed values.
D = Dirichlet predictions.

Scanner panel data from selected American cities provide further evidence, not only within chains but also within stores. The same basic message comes from all these studies: the buying of own labels is not dissimilar from the way other leading brands are bought. Between

chains, or stores, own-label buyers will duplicate their purchases, even to the extent of buying those sold by competing retailers.

What implications are there?

Accurate and usable information is needed if managers are to make effective marketing decisions. Yet all too often only partial information is to hand, and as a result there is a chance that inappropriate strategies are pursued. For instance, decisions based on the popular belief that consumers buy own labels selectively could be damaging if the belief is in fact untrue. Our research casts doubt on several *strategic uses of own labels*: that they play a very significant role in building and sustaining store loyalty, that they differentiate stocks in such a way that consumers change their behaviour, and that they compete mostly with minor brands.

Instead, what we find is that many consumers treat own labels just like any other brand: there happen to be some who are loyal ('Safeway own-label buyers'), but most of them have a repertoire. They buy other brands, they buy at other chains, and they buy the own labels of other chains. There is so little difference in the actual record of buying manufacturer brands and own labels that we wonder whether consumers simply see them as equivalent brands.

Another implication of this study is that the performance of own labels can be assessed against *norms*. For example, given that 36 per cent of own-label sales at Safeway come from those who are wholly loyal to this item, should this be seen as 'only' 36 per cent or 'as many as' 36 per cent, or is it just 'about right'? The absolute figure has little meaning without comparable information, such as the theoretical norms. If fewer people than expected are loyal, then this can be identified and positive action taken, such as in-store promotions or the use of redeemable coupons.

This study does not imply that an own-label strategy is of no benefit to the retailer – it might well help to reinforce sales at a successful store. What it cannot be expected to do is buck the trend; own labels sold through an ailing store will simply take on the persona of the store unless there is a more radical turnaround of the whole business.

Apart from these consumer-oriented aspects, there may be financial and operational benefits too. For example, more control over price, quality, stock assortment, and shelf allocation, coupled with higher gross margins, all of which should feed through into higher profits. These potential benefits, however, must be set against the costs and risks that head office faces when it takes on the task of selling own labels.

In this study the emphasis has been on *how* people buy brands and

own labels before attempting to discover why they do so. This is by no means the full story, and attitude surveys and consumer experiments are in progress to gain a deeper knowledge of this process. Altogether, this work holds out the prospect of providing retailers with some factual evidence on which to base their future marketing strategies for brands and own labels.

References

- Aske Research (1976) *The Structure of the Biscuit Market*, mimeo, London Business School.
- Charlton, P. (1973) 'A review of shop loyalty', *Journal of the Market Research Society* 15: 25–41.
- Chernatony, L. de (1988) 'The impact of the changed balance of power from manufacturer to retailer in the UK packaged groceries market', in this volume.
- Cunningham, R.M. (1961) 'Consumer loyalty to store and brand', *Harvard Business Review* 39: 127–37.
- Ehrenberg, A.S.C. (1988) *Repeat-Buying: Theory and Applications*, 2nd edn, London: Griffin, New York: Oxford University Press.
- Ellis, K. (1989) 'Private label buying behaviour in the package grocery market', unpublished PhD dissertation, London Business School.
- Euromonitor (1984) *The Own Brands Report*, London: Euromonitor Publications Ltd.
- (1986) *The Own Brands Report*, London: Euromonitor Publications Ltd.
- Goodhardt, G.J., Ehrenberg, A.S.C., and Chatfield, C. (1984) 'The Dirichlet: a comprehensive model of buyer behaviour', *Journal of the Royal Statistical Society A* 147: 621–55.
- IPA (1980) *The Growth of Retailer Power*, London: Institute of Practitioners in Advertising.
- Kau, Ah Keng and Ehrenberg, A.S.C. (1984) 'Patterns of store choice', *Journal of Marketing Research* 21: 399–409.
- McGoldrick, P.J. (1984) 'Grocery generics: an extension of the private label concept', *European Journal of Marketing* 18: 5–24.
- Rao, T.R. (1969) 'Are some consumers more prone to purchase private brands?', *Journal of Marketing Research* 6: 447–50.
- Simmons, M. and Meredith, W. (1984) 'Own labels profile and purpose', *Journal of the Market Research Society* 26: 3–27.
- Stoessl, S. (1979) 'Is the real consumer brand of the future the retailer: is shop loyalty taking over from brand loyalty?', *ADMAP* November: 987–90.
- Uncles, M.D. and Ehrenberg, A.S.C. (1988) 'Patterns of store choice: new evidence from the USA', in N. Wrigley (ed.) *Store Choice, Store Location and Market Analysis*, London: Routledge, 272–99.
- Uncles, M.D. and Ellis, K.E. (1989) 'The buying of own labels', *European*

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Journal of Marketing, 23 (forthcoming).

Wrigley, N. and Dunn, R. (1984) 'Stochastic panel-data models of urban shopping behaviour: 3. The interaction of store choice and brand choice', *Environment & Planning A* 16: 1,221-36.

HOW PRIVATE LABELS AFFECT CONSUMER CHOICE

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1 Introduction

Wider consumer choice is an important feature of grocery retailing. Changes in demand, because of awareness about healthy eating and nutrition, and more intense retail competition, have led to an increase in choice. This means that competition is no longer only about price, it is also about attracting customers on the basis of product range, store ambience, parking and the sale of fresher foods.

Of central importance to retail competition has been the role of private labels, to the extent that KwikSave is the only major multiple retailer in the UK not to offer them. Originally cheap, inferior substitutes, private labels are now value-for-money retail brands in their own right. It is said that they help retailers to differentiate their stock from that of the competition, provide higher margins and offer greater operational control. They are also used extensively for product development, be it range extension or new product trials.

Because retailers have tended to rationalise their product range when deciding to offer a private label, the absolute number of different items has rarely risen within traditionally defined product fields. Instead, product fields have been subdivided in an attempt to offer real variety. For example there has been a proliferation of new varieties (curried baked beans), range extensions (chocolate covered wholemeal biscuits), exotic flavours (passion fruit yoghurt), and new product designs (tubular dispenser toothpaste), and wider stockholding more generally, with products such as toiletries and cosmetics offered in larger multiples.

Private labels have played a key role in this development, with the result that currently they account for over 35% of all UK packaged grocery volume sales (AGB 1988).

This paper is concerned specifically with the role of private labels in consumer choice. We address two main questions:

- * Do private labels affect the way people buy within a store ?
- * Do private labels affect the way people choose between stores ?

The paper is in three parts. In the next section, some principles of buyer behaviour are introduced. Then our analyses are presented in sections 3 and 4. The two questions about consumer choice - choice within and between stores - are at the heart of our analyses. Finally, in section 5, we show how our results relate to some wider issues of consumer choice.

2 A Model Of Consumer Choice

We draw on an empirically-based theory of buyer behaviour (Ehrenberg 1988). It is a behaviourist theory which focuses on choice only as it is reflected in actual purchase behaviour.

Intuitively we know that individual buyer behaviour is complex, even for low-involvement decisions. There are pre-purchase needs and attitudes, the experience of previous usage, and external influences such as advertising, promotions and retail availability.

Each time a shopping trip is undertaken, various choices are available and decisions have to be made about what products to buy and where to buy them. This complexity is compounded by the fact that there are many buyers in the market place, each with different needs, values, attitudes and consumption rates. There are many different buying situations and an almost bewildering set of choices and decisions to be made.

Yet despite such complexities at the individual level, simple regularities have been observed at the aggregate level in the purchasing of fast moving consumer goods. In as far as the consumer is dealing with frequently bought, low priced items, the amount of risk involved is low. Differences between items are small and so people develop ways of simplifying the repetitive choice process. And at the aggregate level this means patterns are observed 'as if' behaviour is regular.

We use a model, the Dirichlet model, which successfully describes these patterns. It describes how many households buy a good in a certain length of time and with what frequency; how many are 100% loyal and how many buy from one time period to the next. Typically the model is used to examine the purchasing of brands; however it readily extends to store choice as well.

Two basic assumptions are made in using the model: that the market is stationary and unsegmented. Stationarity, as used here, is the absence of any marked short or medium-term trends. It does not necessarily mean a lack of changing conditions in the market place, or the absence of trends for other items. Rather, that the sum total of all the varying and dynamic marketing inputs (advertising, price, distribution etc), has no overall effect on changing the sales of the item in question during the relevant time period. In practice an approximate degree of stationarity is usually observed.

In an unsegmented market, where all items compete equally, there is no particularly high or low correlation between buyers of one item with those of another over and above what we would expect from their market shares. In practice this is usually what we find in a product field.

We use the Dirichlet model because of its wide applicability in many fast-moving consumer goods markets, and because of its robustness and reliability. Furthermore, with the availability of panel data and software like BUYER (Uncles 1989), it is now easy to use.

The Dirichlet and its predecessor, the Negative Binomial Distribution model (NBD), have been the most successful of the many stochastic models used to reflect consumer purchase behaviour (Morrison and Schmittlein 1988). The Dirichlet was first developed by Chatfield and Goodhardt (1975) and has since been successfully applied to brand, private label and store choice behaviour (Goodhardt et al. 1984, Kau and Ehrenberg 1984, Wrigley and Dunn 1984, Uncles and Ehrenberg 1988, Uncles and Ellis 1989).

3 Analyses

We focus on the main components of sales:

$$\text{Sales Volume} = b \cdot w$$

where b = the proportion of households buying the item in a given time period, the penetration of that item
 w = the average purchase frequency of these buyers

We then elaborate on several aspects of buying in terms of loyalty and switching. This provides a detailed picture of what constitutes aggregate sales.

Panel data are used for 48 weeks of 1985. These are records of what people buy week-by-week. The information is collected by AGB from an in-home audit panel. Several product fields and regions have been studied in order to make extensive comparisons, and ensure the results are not dependent on any particular selection of data. However, for reasons of clarity, we only show results for a couple of product fields and two regions, London and Lancashire.

The retail mix in these regions differs. London is dominated by Sainsbury and Tesco stores, whereas Asda and KwikSave are the major operators in Lancashire. Both the leading retailers in London have extensive private label ranges, whereas KwikSave is a wholly branded operation (Table 1).

Table 1 : Private Label Market Shares Within Stores

Region	Store	Share Of Product Field In Store		Private Label Share In Store	
		FS	FC	FS	FC
Lancashire	KwikSave	18	23	0	0
	Sainsbury	5	4	51	52
London	Tesco	15	14	53	22
	Sainsbury	37	37	72	41
Average		19	20	44	29

Note : FS Fruit Squash; FC Fabric Conditioner Source : AGB (1988)

It should be noted that in our study KwikSave is the only store without private labels. However, we believe that it is indicative of what would be found at similar stores because the buying patterns are closely predicted by the general models.

4 Results

4.1 Do Private Labels Affect The Way People Buy Within A Store

To see whether private labels are bought in a similar way to branded items, we study how many consumers buy Fruit Squash, how often they buy it, and what other items in the product field they buy. We do this for Tesco in London, where private labels are strong, and KwikSave in Lancashire, where they are absent.

Do Private Labels Affect The Number Of People Buying And The Rate At Which They Buy?

Of the two main components of the sales equation, penetration (b) usually varies more than purchase frequency (w). This is seen in the figures for observed (O) and theoretical (T) sales of Fruit Squash at both stores (Table 2).

Table 2 : Penetration And Average Purchase Frequency - Fruit Squash (48 Weeks)

Item	b		w		Item	b		w	
	O	T	O	T		O	T	O	T
KwikSave (Lancashire)					Tesco (London)				
Robinsons	15	(15)	6.0	(6.1)	Tesco pl *	11	(12)	5.4	(5.2)
Vimto	10	(11)	5.9	(5.4)	Robinsons	7	(5)	2.8	(3.7)
Gee Bee	6	(5)	4.2	(4.5)	Quosh	7	(6)	3.4	(3.9)
Sunland	6	(5)	3.7	(4.4)	Rob. Barley	2	(1)	2.8	(3.3)
Kia-Ora	3	(2)	2.3	(4.1)	Others	2	(1)	2.1	(3.3)
Others	1	(1)	1.7	(4.0)					
Average	7	(7)	4.0	(4.8)		6	(5)	3.3	(3.9)

Note : 24 week base used in fitting the Dirichlet model; * Tesco private label.

Tesco private label conforms to the usual pattern and, as a result, it is closely predicted by the model: 12% of consumers are expected to buy the Tesco private label 5.4 times as compared to 11% who actually do so 5.2 times.

In Tesco brand penetration varies from 2% to 11%, whereas purchase frequency varies much less. The same is true for KwikSave, as we would expect from the theory. Nevertheless, smaller brands not only have fewer buyers, their buyers also tend to buy less often. This is the so-called Double Jeopardy effect (Ehrenberg et al. 1988). In fact the observed fall in rates of buying here is greater than what is predicted from the model (this is largely because of the small sample sizes for Kia-Ora, Other Brands and Robinsons Barley).

The only noticeable difference between Tesco and KwikSave (ie. between stores with and without private labels) is that when private labels are offered they usually become the within-store brand leader. Moreover, this has been found for sales of private labels in other product fields (see Ellis 1989).

Do Private Labels Affect Buyers Share Of Requirements?

Here we examine buyers total rate (wp) of Fruit Squash purchasing. Typically, buyers of items with small market shares make the most purchases and this is what we observe for buyers at both KwikSave and Tesco (Table 3).

Table 3 : Product Purchase Rates - Fruit Squash (48 weeks)

Item	wp		Item	wp	
	O	T		O	T
KwikSave (Lancashire)			Tesco (London)		
Robinsons	11	(11)	Tesco pl	8	(8)
Vimto	11	(11)	Robinsons	9	(10)
Gee Bee	10	(14)	Quosh	9	(10)
Sunland	11	(14)	Rob. Barley	15	(11)
Kia Ora	16	(15)	Others	11	(11)
Others	19	(15)			
Average	13	(13)		10	(10)

Note: 24 week base used in fitting the Dirichlet model.

Tesco private label buyers make 8 Fruit Squash purchases in total as compared to the smaller Robinsons Barley whose buyers make 15 purchases. A similar pattern is found in KwikSave. Predictions from the Dirichlet model are close for individual items - in fact the averages are identical - with only a few discrepancies for brands with small market shares.

The difference between w and wp is indicative of the degree of brand switching within each store. Most consumers buy more than one brand of Fruit Squash within a store, especially over longer periods of time. For example of the 8 Fruit Squash (Table 3) purchases made by Tesco private label buyers 5.4 (Table 2) are of the Tesco private label, the remaining 2.6 are of other brands. This is not unusual.

The proportion of all Fruit Squash purchases given to each item in one store is called the local share of requirements. This is derived from the average purchase frequency of a given item (w) as a proportion of the total product field purchasing rate (wp). Usually buyers of items with larger market shares devote more of their total repertoire to the one

item. Buyers of items with smaller market shares tend to be less loyal in this respect. This is found within both the stores that we discuss (Table 4).

Table 4 : Share Of Requirements - Fruit Squash (48 Weeks)

Item	w/wp		Item	w/wp	
	O	T		O	T
KwikSave (Lancashire)			Tesco (London)		
Robinsons	55	(55)	Tesco pl	68	(65)
Vimto	54	(45)	Robinsons	31	(37)
Gee Bee	42	(32)	Quosh	38	(39)
Sunland	34	(32)	Rob. Barley	19	(30)
Kia Ora	14	(27)	Others	19	(30)
Others	9	(27)			
Average	31	(37)		33	(39)

Note : 24 week base used in fitting the Dirichlet model.

In Tesco for example, private label buyers give 68% of all their Fruit Squash purchases to this private label, whereas for Other Brands the comparable figure is 19%. The same pattern occurs in KwikSave. So buyers in both stores devote a similar share of their purchases to individual items and these proportions are as we expect from theory. There is no sign that private labels achieve anything out of the ordinary; they simply behave like any other brand with a similar market share.

Do Private Labels Affect Sole Buying?

Though many buyers switch brands, some remain loyal to one particular item within an analysis period. These are 'sole' buyers whose incidence and rate of buying are denoted as 'bs' and 'ws' respectively. In short time periods there tend to be many sole buyers, but as the time period lengthens the number of these buyers declines. This is because after several weeks the cohort of sole buyers has a greater opportunity to buy other items. Items with small market shares generally have fewer sole buyers than larger items, another Double Jeopardy pattern.

Included among sole buyers are those who make only one purchase, as well as those who buy more often and who are still loyal to one particular item.

There is no marked difference between the two stores, despite Tesco offering private labels (Table 5). But a Double Jeopardy pattern is evident within both stores; for instance, in Tesco stores nearly half of those buying the private label are sole buyers as compared to a third of Quosh buyers.

Table 5 : Incidence And Rates Of Sole Buying - Fruit Squash (48 Weeks)

Item	bs		ws		Item	bs		ws	
	O	T	O	T		O	T	O	T
KwikSave (Lancashire)					Tesco (London)				
Robinsons	40	(36)	5.6	(4.0)	Tesco pl	49	(46)	3.9	(3.7)
Vimto	32	(28)	4.0	(3.3)	Robinsons	24	(25)	2.3	(2.3)
Gee Bee	27	(21)	2.7	(2.6)	Quosh	37	(26)	2.6	(2.4)
Sunland	18	(21)	4.9	(2.5)	Rob. Barley	*	*	*	*
Kia Ora	5	(18)	1.0	(2.3)	Others	7	(20)	1.0	(2.0)
Others	*	*	*	*					
Average	24	(25)	3.6	(2.9)		29	(29)	2.5	(2.6)

Note : 24 week base used in fitting the Dirichlet model; * no sole buyers.

On average the model predictions are reasonably close, although a few large discrepancies appear because of small sample sizes.

The incidence and rate of sole buying is not dependent on whether a store has or does not have a private label. Buying patterns are similar at both stores. So there is no indication of the private label attracting more sole buyers than, for example, the brand leader in KwikSave. The two both have higher levels of sole buying than is predicted.

Do Private Labels Affect Duplicate Buying?

Less than half the customers remain completely brand loyal during the analysis period. The majority also buy other items and are duplicate buyers. They spread their purchases between different items within the product field and have a repertoire of purchases. This is shown by a duplication table (Table 6). For example, in KwikSave 30% of Robinsons buyers also buy Vimto, 24% also buy Sunland, 14% also buy GeeBee and so on.

Table 6 Incidence Of Duplicate Buying - Fruit Squash (48 weeks)**KwikSave (Lancashire)**

Item	R	V	G	S	K	O
Robinsons	*	30	14	24	14	5
Vimto	46	*	24	22	16	0
Gee Bee	38	41	*	16	19	5
Sunland	61	37	16	*	18	3
Kia Ora	67	48	33	33	*	0
Others	83	0	33	17	0	*
Average	59	31	24	22	13	3
Predicted	54	36	22	22	11	4
Deviation	5	-5	2	0	2	-1

Tesco (London)

Item	T	R	Q	R	O
Tesco pl	*	35	28	8	15
Robinsons	56	*	38	16	22
Quosh	47	40	*	14	21
Rob. Barley	60	70	60	*	21
Others	73	67	60	13	*
Average	59	53	47	13	20
Predicted	73	46	46	13	13
Deviation	-14	7	1	0	7

Note : predicted duplication = (the sum of average duplications / sum of average penetrations) * the penetration of each item.

There are two main patterns to note here. First, average duplication declines as penetration falls. In Tesco average duplication falls from 59% to 13%, which is in line with the fall in penetration. The same effect, of smaller brands having fewer duplicate buyers, is also seen in KwikSave.

Secondly, the average duplication is predictable. The correlation of average and predicted duplication is over 99% for both KwikSave and Tesco.

However, fewer than expected buyers duplicate their purchases with the private label: 59% as compared with an expected 73%. Because it is a leading brand, buyers of the Tesco private label concentrate their purchases on this, so there are fewer purchases 'left over' for the buying of other items. This has also been found to occur in other product fields, especially those where private labels have a large market share (Ellis 1989).

Summary

Overall there is no sizable difference in the buying patterns of consumers at a store offering a private label and one that does not. Buying patterns are similar in Tesco to those in KwikSave. Some well-established patterns are observed and on the whole these are closely predicted by the model.

Within a chain the private label tends to be the brand leader. Many factors might explain why this occurs; for example, shelf space allocations, in-store promotions, price etc. However we do not address these issues here. What we can say is that once the private label is established people will add it to their purchase repertoires and buy it just like any other brand with the same market share.

Private labels attract slightly more loyalty than brands in that they have more sole buyers and a lower level of duplicate buying. The brand leader in KwikSave also attracts more sole buying but this is countered by a lower overall level of duplicate buying with very low duplicate purchasing rates (see Ellis 1989).

4.2 Do Private Labels Affect The Way People Choose Between Stores?

We now consider the role of private labels in how people choose which stores to visit for their grocery purchases.

An individual's choice of store will be influenced by many factors: distance and driving time, store image, merchandise assortment, and special services such as car parking. In aggregate, however, there are regular patterns of behaviour and this enables us to describe individual behaviour 'as if' it were random. In effect, all influences are subsumed within each store's market share; so, if many consumers value the ambience or car parking at a particular store, that store will have a higher share of the market than its competitors. In this sense private labels are just one element of the retail mix.

Indeed, it is now known that the same regularities which exist for brand choice are also found to occur in store choice behaviour (Kau and Ehrenberg 1984; Wrigley and Dunn 1984; Uncles and Ehrenberg 1988).

Because many different factors are subsumed within the stochastic Dirichlet model, any consistent deviations from what are now well-established patterns of buyer behaviour point to exceptional influences (Ehrenberg 1988). It has been suggested that private labels are factors which might be regarded as exceptional: they help retailers to differentiate their stock and, thereby, secure competitive advantage (Frank and Boyd 1965; Simmons and Meredith 1984; Euromonitor 1986).

For such a strategy to be effective, the purchase behaviour of consumers must differ from well-established patterns. So we ask whether stores which offer private labels are treated differently by their consumers than those which do not. If there is a difference, this will be seen as a consistent deviation from the model predictions. If, however, there is no deviation, we have to conclude that private labels have no exceptional effect on buying patterns.

When consumers are making choices - whether to visit one store or another - they are usually buying a basket of goods, rather than one item. However, our approach is to examine a variety of product fields, initially doing so one at a time. In further work we are looking at cross-product-field purchasing, and so far it seems that consumers buy in one product field in much the same way as they buy in another.

Do Private Labels Affect The Number Of People Buying And The Rate At Which They Buy?

The way consumers buy goods among stores is very similar to the way they buy goods within stores. In Table 7 we show the numbers buying Fruit Squash at five leading multiples and at a grouping of Other retail outlets. Like leading brands within a store, those multiples which have a larger share of the market not only attract more buyers, their buyers also buy slightly more often. Thus, Asda in Lancashire has almost a fifth of the Fruit Squash market, and customers there buy at twice the rate than at Sainsbury which has only 5% of the market.

Table 7 : Penetration And Purchase Frequency - (48 Weeks)

Fruit Squash (Lancashire)					Fabric Conditioner (Lancashire)				
Store	b		w		Store	b		w	
	O	T	O	T		O	T	O	T
Other	46	(37)	5.6	(7.2)	Other	34	(29)	3.7	(4.4)
Asda	23	(30)	9.0	(6.7)	KwikSave	20	(24)	4.9	(4.2)
KwikSave	24	(30)	8.6	(6.7)	Asda	16	(19)	4.7	(4.1)
Coop	27	(25)	5.8	(6.4)	Coop	17	(16)	3.7	(4.0)
Tesco	14	(15)	6.1	(5.9)	Tesco	10	(12)	4.7	(3.9)
Sainsbury	11	(9)	4.8	(5.7)	Sainsbury	7	(5)	2.9	(3.7)
Average	24	(24)	6.7	(6.4)		17	(17)	4.1	(4.0)

Note : 24 week base used in fitting the Dirichlet model.

Just as within-store buying is predictable from the Dirichlet model, so too are the buying patterns of consumers among stores. On the whole, the levels of penetration and purchase frequency that we expect from theory are fairly close to what we observe. There are some departures but these

are not systematic and so we cannot draw any firm conclusions from them.

That Tesco is a major private label operation does not encourage more or less people to visit, more or less often, than we would expect given its market share. Buying at KwikSave, where no private labels are available, also fits in with the overall pattern.

The results for Fabric Conditioner confirm what is found for Fruit Squash and both sets of results are indicative of what we find in many other product fields (Ellis 1989).

Do Private Labels Affect Buyers Share Of Requirements?

Consumers buying at a named store will meet many of their needs for a product at that store. On average, buyers of Fruit Squash meet some 38% of their requirements at one store (Table 8). Around this average, there is a tendency for larger stores to receive more of their customers purchases than do smaller stores. Thus for Fruit Squash, the proportion is almost 50% at Asda, falling to 26% at Sainsbury, in line with the respective market shares of these stores.

Table 8 : Share Of Requirements - Fruit Squash (48 weeks)

Fruit Squash (Lancashire)			Fabric Conditioner (Lancashire)		
Store	O	T	Store	O	T
Other	37	(40)	Other	49	(52)
Asda	49	(37)	KwikSave	54	(49)
KwikSave	46	(37)	Asda	54	(46)
Coop	33	(34)	Coop	39	(45)
Tesco	34	(31)	Tesco	42	(43)
Sainsbury	26	(29)	Sainsbury	34	(40)
Average	38	(35)		45	(46)

Note : 24 week base used in fitting the Dirichlet model.

The patterns of buying for Fabric Conditioner and the predictions for both product fields support what we have observed for Fruit Squash, especially if allowance is made for the slightly anomalous definition of Other retail stores.

Therefore those stores which stock private labels do not seem to have an exceptional advantage that encourages consumers to meet more of their requirements from the particular store.

Do Private Labels Affect Sole Buying?

We might expect to see the same patterns here as those described for brand choice within stores (Table 5). However, between stores the Double Jeopardy pattern is unclear (Table 9) and the fit of the model is consistently poor. The reason for this does not depend on whether private labels are stocked; despite the different private label strategies adopted by say, KwikSave and Tesco, the incidence and rates of sole buying in both our product fields are almost identical.

Table 9 : Incidence And Rate Of Sole Buying - Fruit Squash (48 weeks)

Fruit Squash (Lancashire)				Fabric Conditioner (Lancashire)					
Store	bs		ws		Store	bs		ws	
	O	T	O	T		O	T	O	T
Other	20	(18)	6.1	(5.4)	Other	34	(35)	3.3	(4.0)
Asda	23	(16)	5.1	(5.0)	KwikSave	31	(33)	5.6	(3.8)
KwikSave	15	(16)	5.9	(5.0)	Asda	30	(30)	5.0	(3.7)
Coop	16	(15)	6.8	(4.7)	Coop	21	(29)	4.7	(3.6)
Tesco	18	(13)	6.3	(4.3)	Tesco	32	(27)	5.7	(3.5)
Sainsbury	23	(12)	6.4	(4.1)	Sainsbury	30	(25)	5.0	(3.3)
Average	19	(15)	6.1	(4.8)		27	(30)	4.4	(3.6)

Note : 24 week base used in fitting the Dirichlet model.

Rather than being a reflection of merchandise differences, the poor fit seems to arise because of trade-area effects. Usually stores are some distance from each other and so a degree of effort is needed to switch. However, within a store, different brands are placed side-by-side on the shelf and it is relatively easy to make a varied selection.

Do Private Labels Affect Duplicate Buying?

On average only 24% of buyers remain loyal to one particular store when they are buying products like Fruit Squash or Fabric Conditioner (Table 9). The remaining buyers switch between more than one store for their purchases.

The patterns that have been established for brand choice within stores are also evident here. High market share is associated with high duplicate buying. Thus, on average, 46% of Fruit Squash buyers also visit Other retail outlets (which collectively have the highest market share), whereas only 9% also visit Sainsbury (which has a low market share). Furthermore, within each column the figures are of a similar order of magnitude, as was the case for the duplicate buying of brands.

Table 10 : Incidence Of Duplicate Buying Across Stores - (48 Weeks)**Fruit Squash : (Lancashire)**

Store	Ot	AS	Kw	Co	Te	Sa
Others	*	22	25	32	14	9
Asda	41	*	17	23	13	9
KwikSave	47	17	*	23	15	11
Coop	52	20	20	*	10	7
Tesco	47	23	26	21	*	11
Sainsbury	44	23	26	21	15	*
Average	46	21	23	24	13	9
Predicted	44	26	23	22	13	10
Deviation	2	-5	0	2	0	-1

Fabric Conditioner : (Lancashire)

Store	Ot	Kw	As	Co	Te	Sa
Others	*	29	20	25	13	10
KwikSave	47	*	18	20	10	7
Asda	43	23	*	25	12	10
Coop	51	24	25	*	20	7
Tesco	44	21	21	35	*	5
Sainsbury	50	20	25	18	7	*
Average	47	27	22	25	12	8
Predicted	46	27	21	23	13	9
Deviation	1	0	1	2	-1	-1

There are a few small deviations between the average observed and predicted duplications. For instance, duplicate buying of Fruit Squash by Asda buyers is less than expected because of the slightly higher level of sole buying. But there are no large systematic differences, and no exceptional effects arising from the decision to stock private labels. Indeed duplicate buying at KwikSave - a store without any private labels - is exactly as predicted. Because of this we can say that our conclusions are consistent with some very general theories of buyers behaviour.

Summary

Buyers at stores offering private labels behave in a similar way to those who buy at stores with no private labels. Private labels do not seem to dissuade people from shopping elsewhere for a particular product, nor are they a guarantor of more loyalty over and above what we expect from knowing their market shares.

Some individuals do remain completely loyal to a particular store when buying an item, but the majority do not. There is no evidence to suggest that those who remain loyal to a particular store buy more private labels than on average. Most people buy different brands and private labels from a variety of stores, each in relation to the market shares of those stores.

Buying between most stores follows some well-established patterns, as evinced by the generally good fit of the Dirichlet model.

5 Discussion

Within a store, the way consumers buy private labels is similar to the way they buy brands. On the whole, private labels are bought in the same way as other brands with comparable market shares. Thus the private label in Tesco is bought in much the same way as the Robinsons brand in KwikSave. There is just a hint of special loyalty to the Tesco private label, and this has been found more widely in those product fields where private labels have an especially high market share.

For the buying of a product at different stores, consumers patronise stores with private labels in a similar way to how they patronise other stores. Although Tesco offers private labels there are no signs that this discourages customers from shopping elsewhere, even for purchases in the same product field. People continue to switch between different stores and items in relation to the market shares.

Though we have only looked at Fruit Squash and Fabric Conditioner, on the whole our findings are consistent in both product fields. Our findings generalise from markets where private labels are strong to those where they are weak, from food to non-food products, from one region to another and for many stores. On-going research shows that similar conclusions can be drawn for the buying of products like Baked Beans, Instant Coffee and Washing Up Liquid, and that this holds in London and Lancashire, and even other countries (Ellis 1989, Uncles and Ellis 1989). It is a sign of the models robustness that the findings can be generalised and predicted in this way.

Where private labels do differ from brands is in their domination of markets within stores. For instance, in most stores where Fruit Squash private labels are stocked, they are the within-store 'brand' leader. And, as with most brand leaders, not only will more people buy, they will do so more often than is the case for smaller brands.

As far as consumer choice is concerned, our results imply that consumers often have private labels in their purchase repertoires, and they take on the role of brand leader. Once they have achieved this position, they are bought in the same way as any item of the same size.

When retailers offer private labels, this does not lock customers into buying at only one store, nor does the absence of them mean poor sales. Asda for example, with a private label, has the greatest share of the Fruit Squash market in Lancashire, but it is closely followed by KwikSave, which has none.

Our method of analysis enables us to describe purchase behaviour once market share has been determined: however, for the future we need to examine how these market shares are achieved especially in comparison to heavily advertised branded competitors. Likely factors include: good value-for-money, more and better shelf positioning, attractive packaging and in-store promotions. It is factors such as these which may account for the success of private labels within stores and which are subsumed in the all-important market shares.

REFERENCES

- AGB (1988), TCA Databank, available from Audits of Great Britain Ltd, Research Centre, West Gate, London W5 1UA
- Chatfield, C. and Goodhardt, G.J. (1975), "Results Concerning Brand Choice", Journal of Marketing Research, 12, 110-113.
- Ehrenberg, A.S.C. (1988), Repeat-Buying: Facts, Theory and Applications, New Edition (Griffin, London; OUP, New York).
- Ehrenberg, A.S.C., Goodhardt, G.J. and Barwise, T.P. (1988), "The Double Jeopardy Effect", Working Paper, available from CMAc, London Business School, Sussex Place, London NW1 4SA .
- Ellis, K. (1989), "Private Label Buyer Behaviour", PhD Thesis, London Business School, Sussex Place, London NW1 4SA (forthcoming).
- Euromonitor (1986), The Own Brands Report, available from Euromonitor Publications Ltd, 87-88 Turnmill Street, London EC1M 5QU.
- Frank, R.E. and Boyd, H.W. (1965) "Are Private-Brand-Prone Grocery Customers Really Different?", Journal of Advertising Research, 5, 27-35.
- Goodhardt, G.J., Ehrenberg, A.S.C. and Chatfield, C. (1984), "The Dirichlet: a Comprehensive Model of Buyer Behaviour", Journal of the Royal Statistical Society A, 147, 621-655.
- Kau, Ah Keng and Ehrenberg, A.S.C. (1984), "Patterns of Store Choice", Journal of Marketing Research, 21, 399-409.
- Morrison, D.G. and Schmittlein, D.C. (1988), "Generalizing the NBD Model for Customer Purchases: What Are the Implications and Is It Worth the Effort?", Journal of Business And Economic Statistics, 6, 145-166
- Simmons, M. and Meredith, W. (1984), "Own Labels Profile and Purpose", Journal of the Market Research Society, 26, 3-27.
- Uncles, M.D. (1989), BUYER: Buyer Behaviour Software, available from CMAc, London Business School, Sussex Place, London NW1 4SA.
- Uncles, M.D. and Ehrenberg, A.S.C. (1988), "Patterns of Store Choice: New Evidence From the USA", in Store Choice, Store Location and Market Analysis, Ed, Wrigley, N. (Routledge & Kegan Paul, London), 272-299.
- Uncles, M.D. and Ellis, K. (1989), "The Buying of Own Labels", European Journal of Marketing, 23, 57-70.
- Wrigley, N. and Dunn, R. (1984), " Stochastic Panel-Data Models Of Urban Shopping Behaviour: 3. The Interaction Of Store Choice and Brand Choice", Environment & Planning A, 16, 1221-1236.

APPENDIX 13 : Incidence Of Duplicate Buying For Biscuits (48 weeks 1987)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	
	MV	MV	MV	MV	MV	MV	PW	PW	MV	PW	SA	PW	MV	SA	BU	SA	SA	TE	TE	DE	NA	Bu	BU	BU	
MV Digestive	* 50	43	38	28	30	21	21	20	16	13	16	16	16	11	14	10	11	10	9	10	9	8	8	4	0
MV Rich Tea	62	* 39	37	29	34	23	20	21	19	12	16	14	10	10	14	13	11	10	10	10	9	8	4	0	0
MV Wholewheat	59	43	* 40	34	31	22	21	23	17	10	16	21	13	13	16	8	10	8	11	7	8	7	6	0	0
MV Hob Nobb	58	45	44	* 29	32	21	19	24	15	15	17	25	14	14	15	12	12	10	10	10	10	11	5	0	0
MV Jaffa Cake	53	45	48	37	* 30	23	23	23	19	11	19	16	12	12	20	11	10	9	9	9	8	7	4	0	0
MV Ginger Nut	59	54	44	41	31	* 23	24	27	19	12	18	17	9	16	10	10	10	10	10	9	11	8	5	0	0
PW Bourbon Cream	57	50	44	38	32	33	* 41	25	30	11	35	16	10	19	10	9	13	12	11	10	11	11	5	0	0
PW Custard Cream	58	44	43	35	33	34	42	* 24	29	8	33	17	8	17	8	9	12	10	11	9	8	4	0	0	0
MV Fruit Shortcake	59	50	49	46	34	40	26	24	* 17	12	25	19	13	22	11	13	9	11	9	9	9	10	6	0	0
PW Wafers	52	50	40	33	32	32	36	34	20	* 10	32	15	10	19	11	10	14	13	11	8	8	8	4	0	0
SAins Digestive	44	34	25	34	19	20	13	10	14	11	* 10	12	46	9	48	45	13	9	9	9	9	4	3	0	0
PW Jam Ring	57	46	41	40	34	32	44	40	30	34	10	* 16	10	30	11	11	16	13	14	8	10	10	5	0	0
MV Choc Hob Nobb	58	42	57	61	32	32	21	23	24	17	13	16	* 17	18	11	13	8	9	9	9	12	11	0	0	0
SAins Choc Digestive	43	32	38	37	24	19	14	11	17	12	52	11	17	* 13	43	44	10	13	8	8	4	4	0	0	0
BUrton Jam Dodgers	56	47	48	41	42	34	28	25	31	24	11	34	19	14	14	* 49	13	11	8	8	8	4	3	0	0
SAins Finger	41	43	25	32	24	22	16	11	16	14	59	13	13	46	11	50	* 10	9	8	10	3	3	0	0	0
SAins Shortcake	48	37	31	35	21	23	13	14	19	13	57	14	15	49	11	16	12	* 40	12	7	12	5	1	0	0
TEsco Digestive	54	44	30	36	24	28	25	22	16	23	20	24	11	14	15	16	12	* 40	12	7	12	5	1	0	0
TEsco Wholemeal	49	43	43	37	26	27	24	20	21	14	20	13	18	18	18	14	12	41	* 7	6	12	6	1	0	0
DEe Digestive	55	42	29	34	25	25	22	22	18	18	14	22	14	11	17	10	10	12	7	* 11	15	2	0	0	0
NAbisco Digestive	59	48	40	46	29	37	24	22	21	16	18	15	17	15	17	13	15	8	7	14	* 14	4	0	0	0
BUrton Snap Jack	66	50	43	63	32	32	34	24	29	20	11	25	27	10	19	8	6	19	18	24	17	* 11	0	0	0
BUrton Choc Snap Jack	60	46	63	51	35	39	29	24	33	17	13	24	45	15	23	12	11	15	16	7	9	21	* 1	0	0
BUrton Fruit Snap Jack	76	38	57	82	57	43	19	18	0	18	0	0	43	0	0	0	0	58	38	0	0	18	33	* 0	0
Average Predicted	56	45	42	42	31	31	24	22	19	18	20	19	16	16	16	15	15	15	13	10	9	10	6	0	0
D = 1.6	62	50	45	42	32	32	22	22	21	19	18	18	16	16	16	14	14	11	11	11	10	8	5	0	0

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NUMBERING

AS ORIGINAL

REFERENCES

- Aaker, D.A. and Jones, J.M., (1971), Modelling Store Choice Behaviour, Journal of Marketing Research, 8, 38-42.**
- AGB (1988), TCA Databank, available from Audits of Great Britain Ltd, Research Centre, West Gate, London W5 1UA**
- AGB (1985), TCA Reference Manual, available from Audits of Great Britain Ltd, Research Centre, West Gate, London W5 1UA.**
- Akehurst, G., (1983), Concentration In Retail Distribution: Measures And Significance, Service Industries Journal, vol 3, no 2, 161-179.**
- Anscombe, R.A., (1950), Sampling Theory Of The Negative Binomial Distribution And Logarithmic Distributions, Biometrika, 37, 358-382.**
- Applebaum, W., (1966), Methods For Determining Store Trade Areas, Market Penetration And Potential Sales, Journal Of Marketing Research, vol 3, May, 127-141.**
- Aske Research Ltd, (1969-1970), Buying Behaviour Consultancy Reports On A Variety Of Product Fields, available from London Business School, Sussex Place, Regents Park, London NW1 4SA.**
- Banerjee, A.K. and Bhattachayya, G.K., (1976), A Purchase Incidence Model With Inverse Gaussian Interpurchase Times, Journal Of The American Statistical Association, 71, December, 823-829.**
- Barnard, N., Barwise, T.P., and Ehrenberg, A.S.C., (1986), Re-interviews In Attitude Research, Market Research Society Conference, Brighton.**
- Bass, F.M., (1974), The Theory Of Stochastic Preference And Brand Switching, Journal Of Marketing Research, 11, 1-2.**
- Bass, F.M., Jeuland, A. and Wright, G.P., (1975), Equilibrium Stochastic Choice And Market Penetration Theories, Deviations And Computation, Management Science, 22, 1051-1063.**

- Bass, F.M., Kalwani, M.G., Reibstein, D. and Wright, G.P., (1984), An Investigation Into The Order Of The Brand Choice Process, Marketing Science, vol 3, no 4.**
- Bauer, R.A., (1960), Consumer Behaviour As Risk Taking, in Dynamic Marketing For A Changing World, 43rd Conference of the American Marketing Association, ed R.S Hancock, Chicago, 389-398.**
- Bellizi, J.A., Hamilton, J.R., Kruekeberg, H.F. and Martin, W.S., (1981), Consumer Perceptions Of National, Private And Generic Brands, Journal Of Retailing, 52 (Winter), 56-70.**
- Berry, B.J.L. and Garrison, W.L., (1958), A Note On The Central Place Theory And Range Of A Good, Economic Geography, 34,. 304-311.**
- Bird, M and Ehrenberg, A.S.C., (1966), Intentions-To-Buy And Claimed Brand Usage, Operations Research Quarterly, 17, 27-46, and 18, 65-66.**
- Blattberg, R.C., (1980), Evaluation Of Stochastic Brand Choice Models, in Marketing Decision Models, edited by R.L. Scultz and A. Zoltners, New York, North Holland, 183-206.**
- Bond, C., (1984), Own Labels Versus The Brands, Marketing, 8th March, p 22-26.**
- Brown, G.H., (1952 and 1953), Brand Loyalty - Fact Or Fiction?, Advertising Age, 23 (9.8, 30.6, 14.8, 28.7, 4.8, 11.8, 1.8, 22.9, 6.10, 1.12) and 24 (26.1).**
- Carman, J.M., (1970), Correlates of Brand Loyalty: Some Positive Results, Journal of Marketing Research, 7, 67-76.**
- Chaplin, B., and Watkins, T., (1985), Advertising And Own Label Brands, American Marketing Association, New York, December.**
- Charlton, P. and Ehrenberg, A.S.C., (1976), Customers Of The LEP, Applied Statistics, 25, 26-30.**
- Chatfield, C., (1988), Problem Solving, Chapman and Hall.**
- Chatfield, C., Ehrenberg, A.S.C, and Goodhardt, G.J., (1966), Progress On A Simplified Model Of Stationary Purchasing Behaviour, Journal Of The Royal Statistical Society, A, 129, 317-367.**

- Chatfield, C. and Goodhardt, G.J., (1970), The Beta-Binomial Model for Consumer Purchasing Behaviour, Journal of Applied Statistics C, 19, 3, 240-250.
- Chatfield, C. and Goodhardt, G.J., (1973), A Consumer Purchasing Model With Erlang Interpurchase Times, Journal Of The American Statistical Association, 68, 828-838.
- Chatfield, C. and Goodhardt, G.J., (1975), Results Concerning Brand Choice, Journal Of Marketing Research, 12, 110-113.
- Chernatony, De L., (1987), The Impact Of The Changed Balance Of Power From Manufacturer To Retailer In The UK Packaged Grocery Market, Fourth International Conference Of Distribution, Milan.
- Chernatony, De L., (1988), The UK Retail Trade, unpublished PhD thesis, City University Business School, London.
- Coleman, J., (1962), Introduction To Mathematical Sociology, Collier MacMillain, London.
- Cook, V.G. and Herniter, J.D., (1971), NOMAD - Or How Consumers Behave, Sloan Management Review, Spring, 77-79.
- Converse, P.D., (1949), New Laws Of Retail Gravitation, Journal Of Marketing, 14, p 379-384.
- Cotterill, R.W., (1986), Market Power In The Retail Food Industry: Evidence From Vermont, The Review Of Economics And Statistics.
- Cramer, J.S., (1965), Private communication.
- Cunningham, R.M., (1961), Consumer Loyalty to Store and Brand, Harvard Business Review, 39, 127-137.
- Cunningham, R.M., Hardy, A.P. and Imperia, G., (1982), Generic Brand Versus National Brands And Store Brands, Journal Of Advertising Research, 22, October - November, 25-32.
- Davies, K., Gilligan, C. and Sutton, C., (1985), Structural Changes In Grocery Retailing: The Implications For Competition, International Journal Of Physical Distribution and Materials Management, vol 15, no 2, 3-48.

- Dunn, R.S., and Wrigley, N., (1984), Store Loyalty For Grocery Products : An Empirical Study, Area, 16.4, 307-314.
- Dunn, R.S., Reader, S and Wrigley, N., (1983), An Investigation Of The Assumptions Of The NBD Model As Applied To Purchasing At Individual Stores, Applied Statistics, 32 (3), 249-259.
- Dichter, E. (1956), What Are The Real Reasons People Buy Today?, Sloan Management Review, Spring.
- Easton, G., (1976), Patterns of Industrial Buying, unpublished PhD thesis, the London Business School, Sussex Place, London NW1 4SA.
- Easton, G., (1979), Stochastic Models Of Industrial Buying Behaviour, Omega, 8, 63-69.
- Ehrenberg, A.S.C., (1959), The Patterns of Consumer Purchases, Applied Statistics, 8, 26-41.
- Ehrenberg, A.S.C., (1960), A Study Of Some Potential Biases In The Operation Of A Consumer Panel, Applied Statistics, 9, 20-27.
- Ehrenberg, A.S.C., (1965), An Appraisal Of Markov Brand Switching Models, Journal Of Marketing Research, vol 2, 347-362.
- Ehrenberg, A.S.C., and Twyman, W.A., (1966), On Measuring Television Audiences, Journal Of The Royal Statistical Society, A, 130, 1-59.
- Ehrenberg, A.S.C., and Goodhardt, J.G., (1968), A Comparison Of American And British Repeat Buying Habits, Journal Of Marketing Research, vol 5, 29-33.
- Ehrenberg, A.S.C., (1969), Towards An Integrated Theory Of Consumer Behaviour, Journal Of The Marketing Research Society, 11, 305-337, and in Ehrenberg, A.S.C., and Pyatt, F.G., (1971).
- Ehrenberg, A.S.C., and Goodhardt, G.J., (1970), A Model Of Multi-Brand Buying, Journal Of Marketing Research, 7, 77-84.
- Ehrenberg, A.S.C., (1970), A Note On Never Buyers, Journal Of Marketing Research, 7, 536-538.

- Ehrenberg, A.S.C., and Pyatt, F.G., (1971), Consumer Behaviour, London and Baltimore: Penguin Books.
- Ehrenberg, A.S.C., (1972), Repeat Buying: Facts, Theory And Applications, first edition, (North Holland).
- Ehrenberg, A.S.C., (1975), The Structure Of An Industrial Market : The Case Of Aviation Fuel, Industrial Marketing Management, 4, 275-285.
- Ehrenberg, A.S.C. and England, L.R., (1987), Generalising A Pricing Effect, CMAc working paper, available from London Business School, Sussex Place, Regents Park, London NW1 4SA.
- Ehrenberg, A.S.C., (1988), Repeat-Buying: Facts, Theory and Applications, New Edition (Griffen, London; OUP, New York).
- Ehrenberg, A.S.C., Goodhardt G.J. and Barwise, T.P., (1988), The Double Jeopardy Effect, Working Paper, available from CMAc, London Business School, Sussex Place, London NW1 4SA.
- Ellis, K., and Uncles, M.D., (1989), How Private Labels Affect Consumer Choice, in Food Choice And Opportunity - Coping With Change In The Foods System, edited by Brian Beharrell, Cranfield Press, distributed by Pergamon, publication date January 1990.
- Engel, J.F., Blackwell, R.D., and Miniard, P.W., (1986), Consumer Behaviour, CBS Publishing Japan Ltd.
- Enis, B.M. and Paul, G.W., (1970), Store Loyalty As A Basis For Market Segmentation, Journal Of Retailing, 46, 42-56.
- Euromonitor (1986), The Own Brands Report, available from Euromonitor Publications Ltd, 87-88 Turnmill Street, London EC1M 5QU.
- Faria, A.J., (1979), Generics: The New Marketing Revolution, Aakron Business And Economic Review, 10 (Winter), 33-38.
- Farley, J.U., and Ring, L.W., (1970), An Empirical Test Of The Howard-Sheth Model Of Buyer Behaviour, Journal Of Marketing Research, 7, 427-438.
- Fishbein, M., (1963), An Investigation Of The Relationships Between Beliefs About An Object And The Attitude Toward That Object, Human Relations, 16, 233-240.

- Fishbein, M., and Ajzen, I., (1975), Belief, Attitude, Intention and Behaviour, Reading, Mass., Addison-Wesley.
- Fourt, L.A. and Woodlock, J.W., (1966), Early Prediction Of Market Success For New Grocery Products, Journal Of Marketing, 25, 31-38.
- Frank, R.E., (1962), Brand Choice As A Probability Process, Journal Of Business, 35, 43-56.
- Frank, R.E. and Boyd, H.W., (1965), Are Private Brand Prone Grocery Customers Really Different?, Journal of Advertising Research, 5, 27-35.
- Frank, R.E., Green, P.E. and Seiber, H.F., (1967), Household Correlates Of Purchase Price For Grocery Products, Journal Of Marketing Research, February.
- Frank, R.E., Massy, W.F. and Boyd, H.W., (1967), Correlates Of Grocery Product Consumption Rates, Journal Of Marketing Research, May.
- Fulgoni, G.M., (1982), A New Tomorrow For Market Research, Market Research Conference, April 15th.
- Fulop, C., (1983), Retailer Advertising And Retail Competition In The UK, International Journal Of Advertising, vol 2, no 4, 1983, 365-376.
- Gabor, A., (1980), Pricing, London, Heinemann.
- Givon, M., (1984), Variety Seeking Through Brand Switching, Marketing Science, 3, 1-22.
- Givon, M. and Horsky, D., (1978), Aggregated Heterogeneous Brand Choice Behaviour, Management Science, 24, 1404-1416.
- Goodhardt, G.J., Ehrenberg, A.S.C and Chatfield, C., (1984), The Dirichlet: A Comprehensive Model Of Buyer Behaviour, Journal Of The Royal Statistical Society A, 147, 621-655.
- Grahn, G.L. (1969), The NBD Model of Repeat Purchase Loyalty: An Empirical Investigation, Journal of Marketing Research, 6, 72-78.
- Granzin, K.L. (1981), Investigation Of The Market For Generic Products, Journal Of Retailing, 57, (Winter), 39-55.

- Gupta, S., (1986), An Integrated Model Of Interpurchase Time, Brand Choice and Purchase Quantity, unpublished PhD thesis, Columbia University Graduate School Of Business.**
- Gupta, S., (1988), Impact Of Sales Promotions On When, What And How Much To Buy, working paper, Los Angeles Graduate School Of Management, USA.**
- Harary, F. and Lipstein, B., (1962), The Dynamics Of Brand Loyalty : A Markovian Approach, Operations Research, 10, 19-40.**
- Herman, R.I. and Beik, L.L., (1969), Shoppers Movements Outside Their Local Retail Areas, Journal Of Marketing, 32 (October), 45-51.**
- Herniter, J.D., (1971), A Probabilistic Model Of Purchase Timing And Brand Selection, Management Science, 18, p 102-113.**
- Hinshelwood, C., (1957), Presidents Anniversary Address, Proc. Ref. Soc. B, 148, 5-16.**
- Howard, J.A., and Sheth, J.N., (1969), The Theory Of Buyer Behaviour, New York, John Wiley.**
- Irwin, J.O., (1964), The Personal factor In Accidents - A Review Article, Journal Of The Royal Statistical Society, A, 127, 438-451.**
- Jacoby, J., (1978), Consumer Research : A State Of The Art Review, Journal Of Marketing, vol 42, 87-96.**
- J. Walter Thompson (JWT), 1970, Understanding Buyer Behaviour Essays.**
- Jeuland, A.P., (1979), The Interaction Effect Of Preference And Availability On Brand Switching And Market Share, Management Science, vol 25, 10, 953-965.**
- Jeuland, A.P., Bass, F.M and Wright, G.P., (1980), A Multi-Brand Stochastic Model Compounding Heterogeneous Erlang Timing and Multinomial Choice Process, Operations Research, 28 (2), 255-77.**
- Jones, J.M., (1973), A Composite Heterogeneous Model of Brand Choice Behaviour, Management Science, 19, 499-509.**

- Jones, J.M and Zufryden, F.S., (1980), Adding Explanatory Variables To A Consumer Purchase Behaviour Model - An Explanatory Study, Journal Of Marketing research, 17, 3, 323-334.
- Kahn, B.E., Kalwani, M.U., and Morrison, D.G., (1986), Measuring Variety Seeking And Reinforcement Behaviours Using Panel Data, Journal Of Marketing Research, 23, 89-100.
- Kau , Ah Keng, (1981), Patterns Of Store Choice, unpublished PhD thesis, University Of London.
- Kau, Ah Keng and Ehrenberg A.S.C., (1984), Patterns of Store Choice, Journal of Marketing Research, 21, 399-409.
- Kemp, C.D., (1970), Accident Proneness And Discrete Distribution Theory, in Random Counts In Scientific Work, vol 2 edited by G.P. Patil, Pennsylvania State University Press.
- King, S.H.M., (1970), What Is A Brand?, Advertising Quarterly, 24, 6-14.
- Klokkaris, C., (1990), Situational Factors In Consumer Behaviour, unpublished PhD thesis, Cranfield School Of management.
- Kotler, P., (1967), Marketing Management, Engelwood Cliffs, Prentice-Hall.
- Kuehn, A.A., (1962), Consumer Brand Choice As A Learning Process, Journal of Advertising Research, 3, 10-17.
- Lamb, T.J., (1989), Patterns Of Brand And Store Choice, unpublished PhD thesis, City University Business School, London.
- Lamb, T.J., and Goodhardt, G.J., (1988), A Comparison Of Brand Loyalty And Store Loyalty, working paper, City University Business School, number 93.
- Lawrence, R.J., (1980), The Lognormal Distribution Of Buying Frequency Rates, Journal Of Marketing Research, 17, 212-220.
- Leahy, T., (1987), Branding : A Key Marketing Tool, edited by John M. Murphy, McMillan.
- Lipstein, B., (1959), The Dynamics Of Brand Loyalty And Brand Switching, proceedings of the ARF Conference in New York, Advertising Research foundation.

- Livesey, F. and Lennon, P., (1978), Factors Affecting Consumers' Choice Between Brands and Retailer Own Labels, European Journal Of Marketing, 12, 2.**
- Martell, D. (1986), Own Labels: Problem Child Or Infant Prodigy, The Quarterly Review Of Marketing, Summer, p 1-12.**
- Massy, W.F., Frank, R.E. and Lodahl, J., (1966), Good Housekeeping, Buying Behaviour And Personality. Stanford Graduate School Of Business, Working Paper.**
- Massy, W.F., and Morrison, D.G., (1968), Comments On Ehrenbergs Appraisal Of Brand Switching Models, Journal Of Marketing Research, volume 5, 225-229.**
- Massy, W.F., Montgomery, D.B., and Morrison, D.G., (1970), Stochastic Models Of Buyer Behaviour, The MIT Press, Cambridge, Mass.**
- McGoldrick, P.J., (1984), Grocery Generics: An Extension Of The Private Label Concept, European Journal Of Marketing, 18,1.**
- McPhee, W.N., (1963), Formal Theories of Mass Behaviour, Free Press.**
- Mintel, (1976), Own Labels, Market Intelligence Reports, number 12 and number 10.**
- Monopolies And Mergers Commission, (1981), Discounts To retailers, published by HMSO for MMC, House Of Commons, HC 311, session 1980-1981.**
- Montgomery, D.B., (1988), Comment : On Negative Binomial Distribution, Journal Of Business And Economic Statistics, 6, 163-164.**
- Mordern, A.R., (1985), Market Segmentation And Practical Policy Formulation, Quarterly Review Of Marketing, Winter.**
- Morris, D., (1979), The Strategy of Own Brands, European Journal of Marketing, 13 (2), 55-78.**
- Morrison, D.G., (1969), Conditional Trend Analysis : A Model That Allows For Non-Users, Journal Of Marketing Research, 6, 342-345.**
- Morrison, D.G. and Schmittlein, D.C., (1988), Generalising The NBD Model For Customer Purchases: What Are The Implications And Is It Worth the Effort?, Journal of Business And Economic Statistics, 6, 145-166.**

- Munn, H.F., (1960), Brand Perception As Related To Age, Income And Education, Journal Of Marketing, January, 29-34.
- Murphy, P.E. and Laczniak, G.R., (1979), Generic Supermarket Items: A Product And Consumer Analysis, Journal Of Retailing, 55 (Summer), 3-14.
- Myers, D.J., (1967), The Determinants Of private Brand Attitude, Journal Of Marketing Research, February.
- Neslin, S.A., Henderson, C, and Quelch, J., (1985), Consumer Promotions And The Acceleration Of Product Purchases, Marketing Science, 4 (Spring), 147-165.
- Parfitt, J.H., and Collins, B.J.K., (1968), The Use Of Consumer Panels For Brand Share Prediction, Journal Of Marketing Research, 51, 131-146.
- Rao, T.R., (1969a), Are Some Consumers More Prone To Purchase Private Brands?, Journal Of Marketing Research, 6, 447-50.
- Rao, T.R., (1969b), Consumer's Purchase Decision Process : Stochastic Models, Journal Of Marketing Research, vol 6, 321-9.
- Retail Business, (1971), The Development Of Own Brands In the Grocery Market, no 166.
- Rosen, D.L. (1984), Consumer Perceptions Of Quality For Generic Grocery Products : A Comparison Across Product Categories, Journal Of Retailing, 60 (Winter). 64-80.
- Rothe, J.T., and Lamont, L.M., (1973), Purchase Behaviour And Brand Choice Determinants, Journal Of retailing, vol 49, no 3, 19-34.
- Rushton, A., (1982), The Balance Of Power In A Marketing Channel, 17-38, in Profitable Co-Operation Of Manufacturers And Retailers: The Contribution Of Research, paper at ESOMAR seminar, Brussels.
- Sabavala, D.J., (1988), Comment, Journal Of Business And Economic Statistics, vol 6, no 2.
- Shoemaker, R.W., Staelin, R., Kadane, J.B., and Shoaf, F.R., (1977), Relation Of Brand Choice To Purchase Frequency, Journal Of Marketing Research, 14, 458-468.

- Simmons, M and Meredith, W., (1984), Own Labels Profile and Purpose, Journal of The Market Research Society, 26, 3-27.**
- Stern, L.W., (1966), The New World Of Private Labels, California Management Review, 43-50.**
- Stern, P., (1990), Doctors Prescribing Behaviour, unpublished PhD thesis, London University.**
- Styan, G.P.H. and Smith, H., (1964), Markovian Chains Applied To Marketing, Journal Of Marketing Research, 50-55.**
- Sudman, S., (1964a), On The Accuracy Of Recording Of Consumer Panels : 1, Journal Of The Market Research Society, May.**
- Sudman, S., (1964b), On The Accuracy Of Recording Of Consumer Panels : 2, Journal Of The Market Research Society, August.**
- Sudman, S. and Ferber, R., (1979). Consumer Panels, American Marketing Association, Chicago.**
- Swan, J.E., (1974), Price Product Competition Between Retailer And Manufacturer Brands, Journal Of Marketing, 52-59.**
- Uncles, M.D., (1985), Models Of Consumer Shopping Behaviour In Urban Areas : Analysis Of The Cardiff Consumer Panel, unpublished PhD thesis, University Of Bristol, BD8 1SF.**
- Uncles, M.D (1988), BUYER: Buyer Behaviour Software, available from CMAc, London Business School, Sussex Place, London NW1 4SA.**
- Uncles, M.D. and Ehrenberg A.S.C., (1988), Patterns of Store Choice: New Evidence From The USA, in Store Choice, Store Location and Market Analysis, Ed, Wrigley, N. (Routledge & Kegan Paul, London), 272-299.**
- Uncles, M.D., and Ehrenberg, A.S.C., (1989), Industrial Buying Behaviour : Aviation Fuel Contracts, Journal Of Industrial Marketing,**
- Uncles, M.D. and Ellis, K., (1989a), The Buying Of Own labels, European Journal of Marketing, 23, 57-70.**

- Uncles, M.D., and Ellis, K., (1989b), Own Labels : Beliefs And Reality, in Retail And Marketing Channels: Economic And Marketing Perspectives On Producer-Distributor Relationships, edited by Luca Pellegrini and Scrinvas K. Reddy, Routledge.
- Wellan, D.M., (1985), Repeat Buying In Non Stationary Markets, unpublished PhD thesis, London University.
- Wellan, D.M., and Ehrenberg, A.S.C., (1988), A Successful New Brand : Shield In The UK, Journal Of The Market Research Society.
- Wheatly, J.J. and Jones, B., (1983), Exploring The Question Of Why Consumers Don't Buy Generics, in Murphy, P.E. et al (eds), AMA Educators Proceedings, Chicago, American Marketing Association, 5-10.
- Wierenga, B., (1974), An Investigation Of Brand Choice Processes, University Press, Rotterdam.
- Wilks, S.S., (1962), Mathematical Statistics, New York, Wiley.
- Williamson, E., and Bretherton, M.H., (1964), Tables Of The Logarithmic Series Distribution, American Mathematics And Statistics, 15, 284-297.
- Wray, M. (1983), Marketing, 15th September, p 47-50.
- Wrigley, N., (1988), Store Choice, Store Location And Market Analysis, edited by Neil Wrigley, Routledge, London and New York, Chapter 1, Retail Strategy And Retail Analysis, 3-34.
- Wrigley, N., and Dunn, R., (1984a), Stochastic Panel Data Models Of Urban Shopping Behaviour : 1 Purchasing At Individual Stores In A Single City, Environment And Planning, A, vol 16, 629-650.
- Wrigley, N., and Dunn, R., (1984b), Stochastic Panel Data Models Of Urban Shopping Behaviour : 2 Multistore Purchasing Patterns And The Dirichlet Model, Environment And Planning, vol 16, 759-778.
- Wrigley, N. and Dunn, R. (1984c), Stochastic Panel-Data Models Of Urban Shopping Behaviour :3. The Interaction Of Store Choice and Brand Choice, Environment & Planning A, vol 16, 1221-1236.
- Wrigley, N., and Dunn, R., (1984d), Stochastic Panel Data Models Of Urban Shopping Behaviour : 4 Incorporating Independent Variables Into The NBD And Dirichlet Models, Environment And Planning, A, vol 17, 319-331.

Yankelovich, D., (1964), Market Segmentation, Harvard Business Review, vol 42, 83-90.

Zufryden, F.S. (1978), An Empirical Evaluation of a Composite Heterogeneous Model of Brand Choice And Purchase Timing Behaviour, Journal of Business, 24 (7), 761-733.