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**PATTERNS OF PHARMACEUTICAL PRESCRIBING**

**Philip Stern**

**A Thesis Submitted in Partial Fulfilment of the  
Requirement of the Degree of Doctor of Philosophy**

**London Business School**

**University of London**

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**ABSTRACT**

This is an empirical study of how general practitioners prescribe ethical pharmaceuticals in the UK. The focus is describing and modelling rather than explaining the prescribing patterns.

The study draws upon two stochastic models, the Negative Binomial Distribution and the Dirichlet. These were originally developed in response to empirical regularities observed in grocery markets and have evolved into a substantive theory of buyer behaviour. Panel data for two pharmaceutical product fields and eight different medical diagnoses are analysed.

In order to describe the patterns, various measures of behaviour are calculated: the number of doctors prescribing each drug and the rate at which they prescribe; the distribution of light and heavy prescribers; the incidence of sole prescribing; and the way in which doctors spread their prescription needs across the different drugs available.

The analysis consists of five elements. Firstly the empirical regularities of prescribing behaviour are explored and then these are modelled with the NBD-Dirichlet at the product field level and then at the diagnosis level. Fourthly, prescribing behaviour of branded pharmaceuticals is compared with that of their generic equivalents. Finally, a single brand which exhibits consistent deviations from the model is studied in some detail to explain why it is different.

There are many similarities between pharmaceutical prescribing and buying groceries despite the extensive differences in the structure of the markets. For example, doctors neither pay for nor consume what they choose to prescribe, and they are trained to make particular choices. The Dirichlet model predicts the components of a drug's prescription share very well. It also predicts product field prescribing behaviour by aggregating data at the diagnosis level.

The analysis reveals differentiation with respect to diagnosis which varies between the two product classes. There is also a tendency for doctors who prescribe a specific drug for one diagnosis to be slightly more inclined to prescribe it in another diagnostic situation. In general there are no differences in the way that branded and generic drugs are prescribed.

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Finally I would like to thank Vikki and my children who provided the means to the end.

**\* For Kenneth Stern, a wonderful father \***

"The most important thing that man has to offer, is a happy face"

Albert Einstein

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### **1.1 Introduction**

This chapter sets the academic context of the thesis, and describes how this research adds to the understanding of markets and marketing.

In contrast to the dominant marketing science tradition which is partly driven by the goal of novelty, this thesis forms part of a 'research programme' (Lakatos and Musgrave 1970, Lakatos 1978). It utilises the Empirical then Theoretical then Empirical (ETE) approach of Ehrenberg (1993) in a new context in order to extend knowledge of marketing. It also makes a contribution in its own right through the new knowledge it derives.

Section 1.2 describes the methodological foundations, and Section 1.3 examines the types of buyer behaviour research in marketing. The next three Sections (1.4, 1.5 & 1.6) look critically at the modelling assumptions, theoretical traditions and outputs of marketing science research, and then Section 1.7 provides the rationale for choosing NBD-Dirichlet modelling in this thesis. Section 1.8 provides a brief review of the development of Ehrenberg's ETE approach and the resulting application to marketing knowledge. This provides a practical evaluation of the method adopted by this thesis.

Sections 1.9 and 1.10 describe the contribution made by the current research to marketing in terms of applying existing knowledge to a new market, and extending existing knowledge about issues such as market structure, branding and segmentation.

Section 1.11 lists the areas of new knowledge derived from the present research. It explains how analyses of usage situation, the role of distribution, the size of the 'buying unit', and the very short inter-purchase timings of the pharmaceutical industry provide new insights into the

patterns of buyer behaviour and market structure. This section also describes the case of one single brand which does not conform to the predicted pattern, and is therefore intrinsically interesting. The section also explores issues of portfolio size and the importance of favourite brands. The chapter concludes with a short summary.

## **1.2 Location of this Thesis in Marketing's Research Traditions**

The debate surrounding appropriate research methods in Marketing has drawn extensively upon the literature of the History and Philosophy of Science. Hunt (1983) proposes the logical empiricist approach after Popper (1959). Day and Wensley (1983) utilise the paradigm shift concept of Kuhn (1962) to describe developments in Marketing Strategy Research. Leong (1985) makes use of Scientific Research Programmes and the Sophisticated Methodological Falsification approach of Lakatos (1978) to explain conflicts in marketing theory. Peter and Olson (1983) believe that the Constructivist philosophy of Feyerabend (1980) most accurately describes the progress of theory development and research in Marketing.

A complete discussion of the appropriateness of such specific approaches is outside the scope of this thesis but it is useful to locate the current research in a methodological context.

The current study aims to develop the approach of describing and understanding buyer behaviour established by Ehrenberg (1959, 1972, 1988). It explores the pharmaceutical market, which is characterised by many significant differences compared to the numerous consumer goods markets previously studied (these differences are detailed in sections 1.10 and 1.11 below). The thesis has three key objectives. Firstly, it aims to establish the patterns of prescribing behaviour of general practitioners. Secondly, it aims to confirm or refute the hypothesis that the ethical pharmaceutical market behaves like previously studied fast moving consumer goods

markets. In these cases, market shares have proved to be the dominant determinant of measures of buyer behaviour. Thirdly, it aims to discover which factors do not influence prescribing behaviour, in order to flesh out an understanding of this market.

The data source and analysis techniques used, together with the location within an established tradition place the research as Sophisticated Methodological Falsification (SMF). This view of science, developed by Lakatos (1978), offers the potential to synthesise the apparent discrepancy between empiricism and relativism (Leong, 1985).

SMF sees science in terms of research programmes and holds that while theories cannot be proved, they can be disproved. Refuting evidence for one theory, however, does not in itself disprove a research programme, which by definition consists of a series of theories. Refuting one theory, therefore, does not invalidate the whole programme.

A research programme has a set of guiding questions it seeks to answer. It has a "positive heuristic" which proceeds in the presence of empirical irregularities as these are not seen as decisive in refuting the programme.

The Empirical then Theoretical then Empirical (ETE) approach of Ehrenberg (1993) fits this profile and in addition distinguishes between the method of research and its aim. In this approach, empirical research suggests theory to account for observations. The theory is then developed conceptually and prescribes further empirical work which in turn further develops the theory. The method utilises falsification but the aim and positive heuristic is to find empirical patterns which hold in a plethora of different situations, and therefore in a "general sense".

### **1.3 Buyer Behaviour Research in Marketing**

The majority of research papers and books published in the field of Consumer Behaviour seem to rely on the development

of conceptual frameworks in order to deduce or induce relationships between attitude and behaviour. These frameworks have not proved susceptible to generalised empirical testing and therefore their value to marketing practice is questionable. It has, however, been argued that empirical testability is too rigid a criterion for theory evaluation, (Morgan and Smircich, 1980) and that the very nature of research in this field makes such tests inappropriate due to three key criteria:

- a) The impracticality of large scale data collection.
- b) The multiplicity and specificity of situation variables which cannot be generalised.
- c) The problem of time and changing inputs.

These issues arise because many academics are interested in explaining causal relationships in advance of describing what is observable but writers such as Peter (1981) stress the importance of description in research.

The most widely quoted consumer behaviour models are probably those of Howard and Sheth (1969) and Engel, Blackwell and Kollat (1978). The latter model (EBK) has some 23 variables which interact to determine an individual purchase but the authors do not provide the means to operationalise the model by specifying how one could measure the variables, their form and interrelationships.

Zaltman and Wallendorf (1983, p. 623) list ten criteria against which models should be evaluated:

1. capacity for explanation and prediction
2. capacity for generalisation
3. heuristic power
4. unifying power
5. internal consistency
6. originality
7. plausibility
8. simplicity
9. supportable by fact
10. testability and verifiability.

It is clear that the complete models referred to above cannot be described as simple, neither have they been verified (Engel, Blackwell and Kollat 1978 p. 559). Indeed, in empirically testing the Howard and Sheth model, Farley and Ring (1974) concluded that the estimates produced by the model for exogenous marketing variables were:

'disappointing because there is only one statistically significant relationship among the four variables involved' and that 'The significance of the coefficient is somewhat surprising, since there is very little variability in the (price) series - in fact, just barely enough to permit its inclusion in the analysis'. (p.149)

It is unclear that these models satisfy any of the above criteria, and in fact they could be used to draw conclusions which are inconsistent with consumer behaviour. Engel, Blackwell and Kollat (1978) applied their model to detergent purchasing and concluded that:

'It becomes difficult under this type of decision making based on strong brand loyalty to induce a brand switch through marketing efforts'. (p. 38)

The 'fact' in this case (ie that brand loyalty exists in this market), is used to support the model. Ehrenberg (1972) and Jeuland, Bass and Wright (1980), however, point out that numerous studies of fast moving consumer goods have shown 100% brand loyalty to be the exception for the vast majority of consumers.

The reason for the popularity of these complete models cannot stem from their managerial or research utility and in the case of Engel, Blackwell and Kollat (1978), they state that:

'pedagogical considerations were the primary motivation for the 1968 and 1973 versions...' (of the model) (p. 559)

This rationale makes the widespread adoption of such models even more of a puzzle!

The lack of utility of such models encourages the examination of alternative tendencies in marketing research which provide a more realistic insight into consumer behaviour and arguably the most fruitful area is that of stochastic modelling. The simplest of these models is probably the Markov brand switching matrix, which is widely quoted in marketing textbooks (eg Kotler 1984, p. 214). The three key limitations of this model have been described by Ehrenberg and Goodhardt (1979). Firstly, the model assumes that consumers exhibit homogeneous repeat-buying and brand-switching behaviour but the evidence shows that consumers differ in these respects. Secondly, the model assumes that the repeat-buying of a brand and the propensity to switch to another brand is independent of the brand's market share, and here the empirical evidence directly contradicts the model's assumption with the market share being a key determinant of repeat-purchase and brand-switching. Finally, the model is based on the analysis of an individual consumer's sequence of purchases within a product field and because individual consumers buy at different rates their purchase sequences are never in phase. This means that it is impractical to aggregate the results and compare brand performance across a product field.

Most marketing scholars categorise models according to whether they explore the incidence of product class purchase or choice between brands. Other classes of model which have received research attention include probabilistic approaches which include exogenous variables to explain brand choice.

There have been a number of models which fit statistical distributions to consumer purchasing data. One example is the Negative Binomial Distribution (eg Ehrenberg 1972) which has been applied to a multiplicity of product fields in a variety of countries. Others are the Condensed Negative Binomial Distribution which was originally proposed by Chatfield and Goodhardt (1973) and the Lognormal

Distribution applied to purchase incidence in the US dentifrice market (Lawrence 1980).

These models restricted analysis to a single entity at any one time and were somewhat limiting when trying to examine buyer behaviour in markets characterised by brand competition. Development into brand choice models was started by Ehrenberg as early as the 1960s and similar models have been proposed (in various forms) by other researchers. These have taken up much of the space in learned journals like Marketing Science and the Journal of Marketing Research since 1980. Evaluating these diverse prior techniques in order to see which might be applicable to a new research situation would depend upon the nature of the problem to be solved and also the researcher's perspective and beliefs. If, for example, the researcher believed:

'A considerable body of evidence shows that choice probabilities are influenced by marketing and other variables... Such explanatory variables therefore must be included in any analysis of brand switching behaviour'

Vilcassim and Jain (1991, p. 29)

then they would discard the use of pure stochastic approaches which assume zero order purchase behaviour. However, the empirical evidence (eg Ehrenberg 1988) does not support Vilcassim and Jain's assumption and in fact shows the opposite to be true.

Categorising the competing models which have appeared in the literature is an onerous task which is outside the scope of this thesis, but the following section provides a simple taxonomy of the published research in the area.

#### **1.4 Modelling Assumptions of Marketing Science Research**

So far, this chapter has described the methodology adopted in the current research and also examined the reasons for using a stochastic modelling rather than a 'conceptual' approach. In this and the next two sections, the key features of marketing science research are examined in order to provide a framework for selecting a specific model. This selection process is the subject of **Section 1.7**.

There are a number of features which contrast approaches and could form the basis of a simple taxonomy of knowledge in the area. The three elements which seem to distinguish research in the mathematically based modelling area of marketing are the assumptions used, the theoretical tradition and the results achieved. Each has further aspects which are listed in table 1.1 and discussed in turn immediately below.

**Table 1.1 A Simple Taxonomy of Marketing Science Research**

<p><b><u>1. Modelling Assumptions</u></b></p> <ul style="list-style-type: none"> <li>a. Nature of the buyers</li> <li>b. How the market works</li> <li>c. Nature of the buying process</li> <li>d. Market dynamics</li> </ul> <p><b><u>2. Theoretical Traditions</u></b></p> <ul style="list-style-type: none"> <li>a. How to conduct the research</li> <li>b. Research objectives</li> <li>c. Research data</li> <li>d. Model inputs</li> <li>e. Confirmation</li> </ul> <p><b><u>3. Research Outputs</u></b></p> <ul style="list-style-type: none"> <li>a. Results</li> <li>b. Significance.</li> </ul>
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#### 1.4a Nature of the buyers

In the 'Marketing Science' tradition there is agreement that consumers should be treated as heterogeneous when modelling their purchase incidence and brand choice (eg Bass, Jeuland and Wright, 1976; Goodhardt, Ehrenberg and Chatfield, 1984). However, where researchers include marketing mix elements as a deterministic part of the model, they assume that consumer response to these variables is homogeneous and they account for heterogeneity at the brand level (see for example Guadagni and Little, 1983). There are other examples where pure stochastic modellers split their markets into separate homogeneous groups of consumers based on prior assumptions about their behaviour and an example here is found in Colombo and Morrison (1989). Little if any generalisable and applicable knowledge has derived from models which include elements of homogeneity. This is unsurprising given the empirically well established patterns of heterogeneity.

#### 1.4b How the market works

The dominant tradition in 'Marketing Science' has been to use pure probabilistic approaches to model consumer choice. These models exclude marketing variables when estimating parameters. When attempts have been made to generate more complete models, Lilien, Kotler and Moorthy (1992) identify two problems:

'First, the inclusion of these additional phenomena lead to models that are analytically complex and difficult to communicate. Second, these models require more data and more subtle estimation procedures than are often available for practical applications' (p. 58)

In the developing models which incorporate explanatory variables, the widely accepted landmark is the logit model of Guadagni and Little (1983). This incorporates price, promotion and a loyalty variable as determinants of brand choice. The comments of Lilien and Kotler may

help explain why this model and its derivatives have not been adopted by practitioners. A further reason may be that subsequent research using this framework has, again, not derived any generalisable findings. Here then are two important reasons for rejecting such an approach when choosing a method to investigate prescribing behaviour.

#### 1.4c The Nature of the Buying Process

Market modellers are split between those who assume that each purchase made is independent of the previous purchase in terms of both timing and choice (eg Ehrenberg, 1988) and those who believe that purchase incidence may be non-random (Morrison and Schmittlein, 1988) or others who believe that previous purchases either reinforce subsequent behaviour (eg Kuehn, 1962) or make consumers seek alternatives (eg Lattin and McAlister, 1985).

These latter non-zero order models are more complex than pure zero-order models such as the Dirichlet. In addition, they have not provided generalisable findings or empirical predictions about buyer behaviour. On the other hand, the Dirichlet has demonstrated success in predicting, for example, the degree of loyalty that a brand attracts in a market as measured by the average proportion of product class purchases a specific brand accounts for. These predictions are based solely on market share measures and require no analysis of, say, purchase runs.

#### 1.4d Market Dynamics

The way of modelling markets is crucially affected by assumptions about the presence or absence of sales trends. Guadagni and Little (1983) examine the (local) market shares of coffee brands and conclude that:

'a panel of 100 households shows great variation over a year's time both in overall trend and specific peaks' (p. 206)

These variations are then used as a justification for building an explanatory model to account for these trends. It is by no means clear from their research that the overall trends show great variation, and they did not pursue the alternative strategy of assuming overall stationarity and then interpreting variations from the stationary norms in terms of conditional expectations (Morrison, 1969). Other modellers also assume that markets are dynamic (see for example Fader and Lattin, 1992) without testing for stationarity. The reasons for this seem to be that the data utilised are analysed in a dynamic sense of switching between brands rather than looking at summary measures of, say, mean rates of purchase recorded in different time periods along with the variances from those means.

## 1.5 Theoretical Traditions of Marketing Science Research

### 1.5a The Question of how to conduct the research

A sample of over 30 papers from the Marketing Science literature (excluding any which were published by Ehrenberg) were examined. Of these, only 2 (Easton, 1980<sup>1</sup> and Frank, 1962) started with data and drew conclusions or developed a model from the data. All the others started with either hypotheses, theories or assumptions, and then went on to develop a model consistent with these pre-conceptions.

All the models developed in these papers were different and claimed superiority in one sense or other (the reason for their production). The opposite approach is to start with data, analyse it to discover patterns and then develop a model to reflect the empirical findings. This model is then further tested on a wide variety of

Footnote: <sup>1</sup>Easton's paper was based on his PhD thesis which was supervised by Ehrenberg.

different data sets to see how far, if at all, the model can be generalised and improved. This approach has been followed by Ehrenberg (almost in isolation) for the last 25 years.

#### 1.5b Research objectives

Most of the modelling research aims to explain a specific marketing situation. For example, the underlying reasons for the (supposed) non-stationarity referred to in **Section 1.4d** above. In the Guadagni and Little example (1983) this would equate to identifying variables to explain the phenomenon. In the selection of papers referred to in **Section 1.4**, all except four were trying to provide an explanation for the item under study. Of the four, three could be classified as merely trying to describe the situation.

The importance of a descriptive approach has been advocated by Peter (1981), and Ehrenberg (1993) shows it to be an appropriate first step in marketing research in line with the traditions of the physical sciences.

#### 1.5c Research data

An increasing number of studies utilise large scale data comprising actual consumer purchases. However there are others which use either simulated data (eg Lattin and McAlister, 1985; Lehmann, Moore and Elrod, 1982) or experimental data which tends to be small scale (eg Wheat and Morrison, 1990). It is generally agreed that the use of large scale behavioural data is the preferred mode for empirical research.

#### 1.5d Model Inputs

The main research tradition (when measured by publications) can be described as the analysis of purchase sequences or brand switching matrices in order to forecast subsequent brand choice and hence market shares via a model.

This approach is driven by the dominant research objective of explaining apparently dynamic marketing situations and how the new steady state came about. This is in sharp contrast to the model inputs for stationarity where, by definition, market shares will be constant in subsequent time periods. Here, market shares are used to derive a multiplicity of measures of brand and product class buying behaviour.

#### 1.5e Confirmation

The dominant practice in marketing science is to test a model against one set of data, or in rare cases, a few sets. In addition, some models are tested against data used in prior research to demonstrate superiority. Most models have not been tested on an extensive range of data, probably because most models are parametised on a single data set and by definition will not work well in other marketing situations. The opposite approach, again typified by the work of Ehrenberg, is to apply a prior model to many data sets in order to see the extent to which generalisations are possible.

### 1.6 Outputs of Marketing Science Research

#### 1.6a Results

The dominant tradition provides the marketing community with novel models which apply to specific situations. The 'scientific' approach of Ehrenberg provides an understanding of novel situations with a specific model. The former provides novelty and the latter new knowledge.

#### 1.6b Significance

The established marketing science tradition measures a model's value in terms of the statistical significance of its fit with observations. The models do not usually provide output which has practical value (eg in explaining variance) or economic value as a basis for managerial prescription. They cannot, therefore, be operationalised and so reside in the pedagogical

category exemplified by the EBK approach to consumer modelling. Out of the sample of papers examined above, only four claimed to have practical and economic significance as an output. All the rest relied on statistical or academic significance as validation.

Table 1.2 summarises the 32 research papers\* in terms of their different foci.

**Table 1.2 Characterising Marketing Science Research**

Percentage of Research papers with specific focus			
	%		
Pure Stochastic	72	25	Stochastic/Deterministic
Pure Heterogeneous	88	12	Non-heterogeneous
Pure Zero Order	59	28	Non zero order
Stationary	59	22	Dynamic
Data led	6	91	Theory led
Descriptive	6	88	Explanatory
Share Input	13	72	Switching/sequence analysis
Observation	72	16	Experiment/simulation
Multiple Data Sets	16	75	Single data sets
New knowledge	12	81	Novelty
Managerial signif.	12	81	Statistical significance

These papers are marked with an \* in the references  
NB Some papers did not have one of the foci being measured.

An alternative characterisation of marketing science research is found in Ehrenberg (1993), where a strong case is made for research which follows the non-establishment model (ie the left hand side of table 1.2).

### **1.7 Choosing a Modelling Approach**

Confronted with a large set of prescription data and how best to utilise this in understanding doctor behaviour specifically and also expand knowledge in a more general sense the researcher can take one of the following routes:

- a) Develop prior hypotheses and develop a model consistent with these hypotheses and then test it against the data (the 'right sided' approach in table 1.2).
- b) Analyse the data in ways which attempt to reveal patterns which have been seen in prior studies in different markets.

If the latter approach is adopted and the previous empirical studies have led to a theory (as in the case of the Dirichlet), then the research can start a step ahead with prior knowledge of the expected patterns.

If no patterns are observed or totally new patterns occur, the task is either to develop a new model, or use an existing one to try and understand the reasons for the difference in data pattern. If, however, the empirical patterns are familiar it is likely that one is examining an incrementally different situation rather than a radically new one and the parsimonious solution is to use an existing model to test goodness of fit (the left handed approach of table 1.2), rather than develop a new model which has no prior empirical grounding.

One would have to be prepared to consider that a set of radically different 'hidden' effects could combine together to produce the similar patterns, but this would not invalidate the suggested method given the objective of description and understanding. Adopting this approach then requires the choice of an appropriate model to help understand the data patterns. The criteria outlined below seem sensible.

- a) The simplest model which will test all the analysed data.
- b) A model which can be easily operationalised.
- c) A model which was developed to describe observed patterns, rather than one which was developed primarily as a conceptual construct and then tested against data to see if the model 'worked'.

- d) A model which will feed back into the understanding of how the pharmaceutical market works.
- e) A model which has demonstrated robustness across an already wide variety of applications.

These considerations lead to the selection of one of the stochastic models of buyer behaviour and brand choice. Most of the published models have not led to general theories developed from empirical observation. This means that they are highly unlikely to have predictive power in the case of a radically new market.

One model which meets all the above criteria and has an empirically rooted theoretical base is the NBD/Dirichlet. Firstly, it can describe all the important previously observed buying patterns with minimal inputs. Secondly, it has been successfully tested in many different product/market situations and thirdly it benefits by virtue of the process in which it was developed, in that it came about in response to a need to understand what might account for patterns of buyer behaviour, and thus its outputs are of practical use to practitioners, being marketing based. Finally, NBD/Dirichlet modelling has developed into a coherent theory of buyer behaviour based on a set of simple assumptions regarding individual purchase and brand choice as well as empirical analysis.

This section has provided a conceptual basis for selecting a model for the current thesis and it is followed by an assessment of the impact of Ehrenberg's ETE approach in order to evaluate the likely practical value in the pharmaceutical market.

### **1.8 The Contribution of Ehrenberg and his Approach to Marketing Knowledge.**

The development of NBD-Dirichlet theory (see Chapter 5) has been gradual, covering some 35 years, and the process termed

"Empirical-Theoretical-Empirical-..." is described in Ehrenberg (1993).

#### 1.8a Development of Dirichlet Theory

The theory developed from a desire to understand regular patterns which appeared when consumer panel data were analysed. It was a case of developing a model (the NBD) to fit the observations and the earliest published research is Ehrenberg (1959). Over the next ten years the model was applied to a large number of different product/markets and at the same time the theory was developed which explained why the model worked. These two streams were brought together in Ehrenberg (1972) which references over 50 published articles authored or co-authored by Ehrenberg and collaborators, dealing with NBD theory and applications.

NBD theory provided marketing practitioners with a way to measure the performance of their brands in relation to other competing brands in their marketplaces. These measures went beyond simple market shares and focussed on the proportion of people who were customers and the frequency with which they purchased. The theory also predicted repeat buying incidence and frequency over different time periods. The model was limited, however, to purchase incidence and did not allow predictions related to brand choice.

An empirical development of NBD patterns into multi-brand buying is found in Ehrenberg (1972) which states:

'Our knowledge of multi-brand buying is far less developed than that of repeat-buying. The empirical results available are far more recent. There is as yet little underlying theory, and so far there are few published practical applications' (p. 175)

The empirical regularities included the observation that buyers of any brand tend to purchase the product class

at an approximately constant rate and the fact that the purchasing of pairs of brands are independent and follow the 'Duplication of Purchase Law'. Work on developing theory to explain these findings was published in 1973 by Chatfield and Goodhardt and by the same two authors in 1975. Nine years later, the Dirichlet theory as it became known, was published by Goodhardt, Ehrenberg and Chatfield (1984). The second edition of Ehrenberg (1988) brought together empirical and theoretical knowledge of multi-brand buying covering a variety of markets and countries.

The practical applications of Ehrenberg's approach to market analysis are found in Ehrenberg and Uncles (1993), but there are other areas where the results of his approach have had a significant impact.

Ehrenberg's focus on understanding buyer behaviour presents insights into markets which run counter to the dominant marketing paradigm of segmentation, targeting and positioning (Doyle, 1989; Kotler, 1984). By examining what people actually do (rather than their stated intentions) Ehrenberg shows how markets tend not to be segmented and that concepts like brand loyalty which drive such a strategy are at the very least unhelpful to the marketer (Ehrenberg and Goodhardt, 1979).

#### 1.8b Applications to the Marketing Mix

Despite the economic importance of price in the marketing mix, little systematic research has been undertaken to measure price elasticity of demand. This is understandable given the problems of isolating price effects from real marketing programmes. One experimental approach involved manipulating prices for a small range of brands and products and observing simple and immediate responses to both changes and returns to 'equilibrium' (Ehrenberg and England 1990).

One inescapable conclusion about viewing markets from a behavioural approach is that brands have buyers with varying purchase frequencies, they do not 'lose and win' buyers. This means that the role of advertising must be different from the accepted rhetoric as illustrated in one of the standard works in the area:

'Advertising in most cases has to repeatedly influence the buyer response sequence in order to initiate purchase [and maintain repeated purchases] of the brand'

Rossiter and Percy (1987, p. 18)

As a result of his analysis of purchase behaviour Ehrenberg has proposed the Awareness Trial and Reinforcement model of advertising which makes far less demands upon advertising's power to influence attitudes and behaviour and sees its role as primarily defensive, and therefore reminding consumers that the advertised brand is one they have used successfully and should consider using again at some point in the future (Ehrenberg, 1974, 1992).

#### 1.8c Impact upon Pedagogy and Practice.

Ehrenberg's robust methodological research approach has resulted in many publications and it is therefore surprising that his view of marketing has yet to effectively challenge the orthodoxy in terms of education and general practice. Ehrenberg himself (1992) suggests it may be to do with the psychological needs of the practitioners:

'American advertising people need to feel that they are influencing consumers in a BIG WAY' (p. 168)

Nonetheless, it remains clear that 'marketing' is not yet ready to abdicate in favour of a 'Dirichlet' world and therefore it is valued less outside the research programme than within.

The position of Dirichlet theory could also be explained as a (thus far) failed paradigm shift. In part this is due to a failure to prioritise dissemination of results in favour of other academic interests between 1977 and 1988. Since then, the research has been re-focussed and geared towards publication in the key academic marketing journals.

The key to a successful paradigm shift (in the context of his own theory) is for Ehrenberg's theory to gain more 'buyers' by further dissemination of the ideas in practical and academic contexts with an increasing network of collaborators and users.

The empirical roots of the Dirichlet together with the marketing mix applications which have resulted more than outweigh its dissemination shortcomings. When one combines these benefits with the conceptual criteria in **Section 1.7** the Dirichlet is clearly appropriate for this research. In order to see the type of market measures and patterns predicted by the Dirichlet, **Section 1.9** describes the generalised knowledge derived from this approach in prior studies.

### **1.9 Prior Studies and the Application of Existing Knowledge**

Prior studies of buying behaviour have been predominantly focussed in fast moving consumer grocery markets due in part to the plethora of available purchase data which covers numerous product fields and geographically dispersed markets. All the research referenced in **Section 1.3** above attempts to model fast moving consumer goods (fmcg) markets. The key text in this area (Ehrenberg 1988) lists some 40 different product fields which have been studied at different times and in different countries over the past 30 years. One model shows how a complete picture of buying behaviour can be built up using simple descriptive marketplace variables.

This research has led to the establishment of empirical regularities (see table 1.3) which, up to a period of a year or two, characterise fmcg markets. It is worth commenting that none of the other approaches published in the literature have resulted in a similar body of knowledge about how stationary markets work.

**Table 1.3            Market Regularities**

- a. Sales of a brand increase predictably with time
- b. Brands differ from each other but in predictable ways
- c. Double Jeopardy is the rule
- d. All brands attract predictably similar loyalty levels
- e. Sole buyers tend to be unattractive in sales terms
- f. Exclusive segmentation tends not to occur

1.9a How sales increase

While by definition, sales of a brand in a stationary market will increase proportionately with time, the percentage of buyers of a brand (its penetration) increases less than proportionately with time because consumers tend to 'repeat-buy' brands. With sales being the product of the number of buyers and how often they buy, this latter term, the average purchase frequency also increases less than proportionately with time (and in most previous studies this term has been shown to grow more slowly than penetration).

1.9b How Brands Differ

The different brands in a product class tend to have a wide ranging number of buyers, whereas the average frequency of purchase varies little. This develops to the generalisation that the product of the average purchase frequency and the proportion of non-buyers of a brand is approximately constant.

### 1.9c Double Jeopardy

Large brands tend to benefit in two ways compared to small brands in that they not only have more buyers, but buyers who buy more often (than do buyers of small brands).

### 1.9d Share of Requirements

An individual brand usually accounts for a minority of the product class purchases of its buyers over the course of, say, a year. Different brands, however, account for similar shares of their buyers' requirements. There is a slight trend for large brands to account for higher shares of their buyers' requirements (than for small brands), therefore attracting higher levels of loyalty when compared to small brands.

### 1.9e The Value of Sole Buyers

The percentage of sole buyers generally decreases with time and such customers tend to buy the particular brand at around the same rate or at a lower rate than the 'average' multi-brand buyer.

### 1.9f Lack of Segmentation

The proportion of buyers of one brand in one period, who also buy a second brand varies directly with the second brand's penetration and usually not with any specific characteristic of the brand. This means that in general, consumer goods markets have been found to lack specific partitions which appeal uniquely to a specific category of customer.

Where 'segments' have been identified (eg families with and without children in the ready-to-eat breakfast cereal market), the partitioning is not exclusive. Families with children buy more pre-sweetened products

than those without children, but are not the sole buyers of this product form (Ehrenberg and Goodhardt, 1979).

The present thesis extends the number and range of situations where these patterns have been found to hold and provides some knowledge about a market which has not been studied in this way before.

### **1.10 The Current Study and Knowledge Extension**

Situations which are characterised differently from fast moving consumer goods markets have received far less attention, but developments in the areas of store choice (Keng and Ehrenberg 1988) and the watching of television programmes (Barwise & Ehrenberg 1988) have extended knowledge into new fields in many countries.

Issues which have been noted but not widely covered by previous empirically based buyer behaviour research include the features listed in table 1.4.

**Table 1.4            Areas of Knowledge Extension**

- |  |
|--|
| <ul style="list-style-type: none"> <li>a. Industrial marketing application</li> <li>b. Focus on individual buyer behaviour</li> <li>c. Buyer behaviour across two product classes</li> <li>d. Brand versus generic buyer behaviour</li> <li>e. Segmentation</li> </ul> |
|--|

#### **1.10a Industrial Market Structure**

One area which has been somewhat neglected is the empirical study of purchase behaviour in industrial markets.

The way in which airlines buy aviation fuel from oil companies has been described by Ehrenberg (1975), and by Uncles and Ehrenberg (1990). Industrial buying of chemicals has been studied by Easton (1980), and the purchasing of executive courses by industrial customers is discussed in Charlton & Ehrenberg (1976). While the

divide between Industrial and Consumer Marketing is less clear than most textbooks tend to describe, it is reasonable to assert that the prescription of ethical pharmaceuticals exhibit elements of the characteristics of an industrial market - eg direct contact between manufacturer and physician, and inelastic demand.

The case of ethical pharmaceutical prescribing in the UK appears radically different from all the other markets previously studied because:-

- The buyer/specifier is not the ultimate consumer.
- In the UK, the "buyer" does not pay for the goods and the vast majority of ultimate consumers either pay a fixed fee which does not relate to the price of the good or receive the drug free of charge.
- The buyer does not become involved in the distribution chain (unless they are one of the small number of dispensing physicians in isolated rural locations).
- The ability of the manufacturer to promote their products to the buyers is limited by law, to the extent that media is restricted. Furthermore, manufacturers are financially penalised if their promotional expenditure exceeds guide-lines laid down by the Department of Health.
- The ethical pharmaceutical industry is one in which new product development can have a significant and rapid effect on a market.

It can be argued that each of these differences are slighter than at first appears in that the first criterion above represents many industrial buying situations, and indeed the person shopping for a household is very likely to purchase goods which will be

consumed by members of the family who were not present at the shopping trip and do not pay for the goods (see **Section 1.10b** immediately below). Many industrial buyers will not find themselves involved in the distribution chain, and the tobacco industry operates in a framework which restricts its promotional activities. Overall, however, the structure is different from the situations studied previously and while one would be able to conclude little if different patterns emerged, similar patterns enable one to begin to conclude that a range of structural differences do not appear to result in different buying patterns.

#### 1.10b The Unit of Analysis

The majority of prior studies of consumer goods describe household buying behaviour because this is the level of aggregation at which the data is collected. Given that only a minority of households are single individuals, it has been suggested that these studies might mask patterns which are unobservable. Khan, Morrison and Wright (1986) tackled this problem from a theoretical stand-point and concluded that panel analyses probably under-estimated individual variety seeking behaviour. However, the key data source of purchasing behaviour which use individuals as the unit of analysis has shown that patterns of television viewing are similar to grocery purchasing (Barwise and Ehrenberg, 1988). In addition, there is nothing to preclude the study of single person households as a separate sample within a consumer panel. In an industrial setting, the aviation fuel contract research of Uncles & Ehrenberg (1990), and Ehrenberg (1975) goes some way to exploring this problem. Another approach has been to simulate individual purchasing behaviour through experiment (see for example Batsell and Polking, 1985).

The current research uses data collected at the individual level and therefore extends our knowledge



about the relevance of the unit of analysis in understanding buying behaviour.

#### 1.10c Cross Product Class Behaviour

A third aspect of purchasing behaviour which seems worthy of further study is how the same buyers behave across different product classes. Ellis (1989) studied purchase behaviour for fruit squash and fabric conditioner, and found some evidence that consumers were more likely to purchase a private label variant in one category if they also purchased the private label variant in the other. The number of duplicate buyers was only around 2% more than predicted (were there no partition) and she concluded that the research was exploratory and required further study.

Ellis also found that when two product fields of similar purchase frequency were combined, the individual brands showed buyer behaviour characteristics as predicted by the Dirichlet.

The present research looks at prescribing behaviour in two different product fields and hence extends knowledge in this area.

#### 1.10d Brand versus Non-brand Buyer Behaviour

Another area which Ellis examined was the patterns of purchase associated with own labels compared to brands. She was confronted by the problem of some consumers never visiting certain retail chains and therefore being unable to purchase those specific private label variants. This 'population at risk' problem is unlikely to disappear from panelised grocery buyer behaviour studies.

In the case of prescribing pharmaceuticals, the population at risk problem is obviated, as the doctor is not normally part of the distribution system.

Nevertheless, a doctor has the choice to write either the brand name or its generic equivalent on the prescription pad, and so the current research provides us with some insights into the differences in the way that doctors prescribe different product forms.

#### 1.10e Segmentation

Some heart complaints frequently require the prescription of more than one pharmacologically active agent. The duplication analysis performed reveals whether any brand pairs show an unusually high propensity for joint prescription. High brand duplications could indicate the type of segmentation which is rarely found in fmcg markets - exceptions being the finding that families with children tend to purchase more pre-sweetened breakfast cereals than do families without children, or the instances of 'me-too' brands, or flavour varieties of the same brand (Ehrenberg and Goodhardt, 1979).

The data upon which this thesis is based enables these five features to be explored as extensions of existing buyer behaviour knowledge.

#### 1.11 The Current Study and New Knowledge

As well as extending our knowledge about established and less well established buyer behaviour issues, table 1.5 lists some areas of this research which are new.

**Table 1.5            Areas of New Knowledge**

- |  |
|--|
| <ul style="list-style-type: none"><li>a. Usage segmentation</li><li>b. The role of distribution</li><li>c. The size of the buying unit</li><li>d. Short inter-purchase timing</li><li>e. A case of breaking the rules</li><li>f. The role of the favourite brand</li></ul> |
|--|

### 1.11a Usage Segmentation

A partially related issue to that of the unit of analysis is that of product usage (McAlister & Pessemier 1982). When a household purchase is recorded in a panel study, the analyst has no means of knowing whether or not the brand was purchased for a specific occasion. For example, instant coffee might be purchased by some households for everyday use, whereas ground coffee might be purchased for the purpose of entertaining. Thus if one was able to look beneath the surface of the data, one might expect to find patterns of behaviour which were dependent upon usage situation.

In the case of ethical pharmaceuticals it may well be that the physician's diagnosis can be contrasted with different consumer usage needs and the present research explores this by relating brand choice to diagnosis.

### 1.11b Distribution Channel

The role of the physician is analogous to that of a retail outlet, which selects the brands which the ultimate user may consume. Unlike the retailer, however, the physician specifies the brand to be consumed and is indifferent to the physical aspects of stocks, such as availability, turnover and return on shelf space.

This research explores whether or not these distribution effects result in different patterns of buying behaviour.

### 1.11c Size of Buying Unit

The buying unit in fast moving consumer goods markets has an average of around 3 members but can vary by a factor of about 10. The present research studies a situation where the physician prescribes for a unit which has an average of around 2000 members but varies by a factor of only about 3. Thus the project explores

whether or not the size of the unit affects the behaviour of the buyer.

#### 1.11d Inter-purchase Timing

A major constraint of prior research studies is the similarity of the inter-purchase times across the many different product fields which have been studied. Groceries tend to be purchased during the weekly shopping trip although most product classes are purchased less frequently than this. Bass et. al. (1976) report annual average purchase frequencies ranging from 27 to 66 for nine different product categories, but most are lower (Ehrenberg, 1988). Other product-market situations which are not described by a weekly cycle tend to have longer purchase times - eg motor oil. The areas which involve shorter inter-purchase times than a week include television, cigarettes and petrol. In the first case, the majority of programming remains weekly (although there are a significant number of daily shows) and in the second, buying behaviour has been found to be somewhat atypical (Ehrenberg, 1988).

Researchers would have welcomed the opportunity to study fmcg markets over a time period longer than a year because markets do change over long periods and hence stationarity assumptions can be violated. However, panel membership problems such as conditioning and attrition increase over long periods, reducing the reliability of the underlying data source.

The issue of analysing very long term data has not yet been tackled but it has been possible to model such markets. Predictions from the Dirichlet, for example, suggest that in the long run the differences between brands will become more marked in terms of their purchase frequency rather than their penetrations.

In this research, two product classes are examined, one which is prescribed once a week on average, and the other which is prescribed four times each week (ie 50 times and 200 times in a year). The latter category allows the predictive power of the Dirichlet to be tested under circumstances where the inter-purchase times would indicate high brand penetrations within the stationary constraint.

#### 1.11e A Case of Breaking the Rules

Over the past 30 years of market analysis, there have been few examples cited of markets which break the established empirical and theoretical rules which arise from the assumptions underlying the Dirichlet. Where deviations are reported they are often due to distribution issues or interpretable in terms of some basic demographic variable. For example, the degree of brand switching between pre-sweetened breakfast cereals is explained by the presence of children in the family buying unit. Such segmentation represents a minor market partition but is by no means trivial.

The current research has discovered one brand of cardiovascular drug which recorded twice the expected average prescription frequency during 1986 - a very large discrepancy.

The theoretical and empirical norms predict that average prescription frequencies should vary little from brand to brand (1.10b) and should follow the Double Jeopardy pattern (1.10c).

Without the form of analysis conducted here, there would have been little of diagnostic significance to relate, but because of the established empirical patterns it is possible to quantify the effect and provide a tentative reason for the variation.

### 1.11f The Role of the 'Favourite' Brand

There has been little published information relating the importance of the favourite brand to the overall portfolio but Wellan (1985) looked at toilet soap and concluded that on average, the favourite brand accounted for 60% of purchases. Another data source would be the "Brand Monitor" tabulations from 'AGB' data. However there has been no published study which describes these patterns.

The present research reports some results in this area showing that there is a relationship between the portfolio size and the importance of the favourite brand in terms of the share it accounts for.

### 1.12 Summary

- The aim of the current thesis is to analyse patterns of prescribing behaviour in order to see if the NBD-Dirichlet model generalises from established applications to a radically different market.
  
- This aim of generalisation is positive, and contrasts with the methodology used which may be characterised as Sophisticated Methodological Falsification.
  
- This approach will also lead to an understanding of the factors which appear not to influence prescribing behaviour.
  
- Stochastic approaches are appropriate for describing and understanding the pharmaceutical market given the problems associated with 'complete' buyer behaviour models.
  
- Traditional marketing science research, with its focus on novelty, is rejected in favour of the "Empirical then Theoretical then Empirical....." approach with its emphasis on discovering new knowledge.

- The choice of the NBD-Dirichlet is justifiable on conceptual and practical grounds, and also provides a way of furthering the development of the "ETE..." process.
- The thesis not only applies an established theory to a new market, but extends knowledge about market structure, branding and segmentation.
- This thesis also derives areas of new knowledge about buyer behaviour patterns such as usage segmentation, the role of distribution, the size of the buying unit, and the role of the favourite brand.
- **Chapter 2** examines the pharmaceutical market and the data used for the current thesis.
- **Chapters 3 and 4** describe the empirical patterns of prescribing behaviour.
- The NBD-Dirichlet model is described in some detail in **Chapter 5** and applied to the product class prescribing data in **Chapter 6**.
- The extensions of knowledge and new knowledge are described in detail in **Chapters 7, 8 and 10**.
- **Chapter 9** considers the reasons why one drug fails to fit the Dirichlet norms. **Chapters 11 and 12** summarise and discuss the results and consider the research implications from the perspective of marketing, practice and future work.

**CHAPTER 2: THE PHARMACEUTICAL MARKET AND THE DATA SOURCE****2.1 Introduction****2.2 Description of the Market****2.3 Description of the Data Collection Method****2.3a Sampling****2.3b What the Panel Measures****2.4 Description of the Data****2.5 Rationale for Product Class Choice****2.5a Desirable Characteristics of the Data****2.5b Therapeutic Area Characteristics****2.6 Stationarity and Seasonality****2.6a Stationarity****2.6b Seasonality****2.7 The Market Definition****2.8 Summary**

## 2.1 Introduction

This Chapter starts by considering the pharmaceutical market and its economic importance. Section 2.3 describes the way that the prescribing data upon which this thesis is based was collected, and looks at issues surrounding the validity of the data.

Section 2.4 describes and provides a summary of the data itself and considers other published studies in the area of drug prescribing. Section 2.5 explains the rationale for the product fields chosen for analysis and Section 2.6 considers the issues of stationarity and seasonality.

Section 2.7 explores the implications of the market definition resulting from this particular data set. The chapter ends with a summary.

## 2.2 Description of the Market

The value of the world pharmaceutical market was about £60 billion in 1986. This figure excludes command economies such as the (then) USSR, China etc. (SCRIP 1988, p. 29). The market has seen consistent real growth to the point where it is worth some £100 billion today.

It is estimated that in 1986 the ten largest pharmaceutical companies had combined sales of some £18 billion and so commanded about 30% of the market. Of these, just one, Glaxo, was controlled in the UK. Six of the top ten were US based multinationals, two were Swiss and the other German. There are around 200 pharmaceutical companies of significant size in the world (SCRIP 1988, p. 41).

In 1986, the UK accounted for 3% of the world pharmaceutical market, and with £1.8bn in sales this makes it the sixth largest geographical market (SCRIP 1988, p. 29). The importance of multinational companies is illustrated by the 1986 revenues of Glaxo which at £1.4bn were larger than the entire Spanish pharmaceutical market (SCRIP 1988, p. 329).

The industry is an important contributor to the UK economy. With exports amounting to £1.5bn contributing to a trade surplus of £850m in 1986, (ABPI, 1987) it employs some 87,000 people (Collier, 1989).

The market is conventionally divided up into therapeutic areas of which there are eleven worth over £1 billion each on a world wide basis. The largest area is cardiovascular which accounts for about 18% of all pharmaceutical sales, and the sixth largest area is musculo-skeletal which account for a further 6% of sales. The market is also traditionally split between prescribing sectors, with hospitals accounting for 28% of the market and general practitioners accounting for the remaining 72% of sales (SCRIP 1988, p. 30).

An alternative estimate puts the proportion of UK pharmaceutical sales accounted for by hospitals at 21%, leaving 79% for general practitioners (Jordan, 1987 p. 11). This figure is confirmed by Collier (1989):

'General Practitioners are the principal target of the drug industry's attentions, because they write 80% of all prescriptions' (p. 29)

The structure of healthcare in the UK means that there are essentially two kinds of prescription. Firstly, the G.P. may prescribe a drug which is not available under the National Health Service scheme, in which case the patient must bear the full cost. An example would be shampoo with Minoxidil which is prescribed to aid the retardation of baldness. Secondly, the doctor will prescribe an item or items under the NHS scheme, in which case the patient will pay either a fixed charge per item (£2.20 in 1986) or if they are classified as exempt for reasons of status or income then no charge at all is made. In 1985 it was estimated that 75% of all NHS prescription items were exempt from charges (SCRIP 1988, p. 253). Assuming the proportion of exempt

prescriptions is reflected in their costs, this means that the net cost of pharmaceuticals to the NHS was some £1.4bn.

The cost of this 'National Drug Bill' has been the subject of controversy and legislation. In June 1983 the government cut the price it paid for drugs by 2.5%, and announced a freeze on prices until 1985. In the same year, Kenneth Clarke, then Minister for Health, stated that the Government aimed to reduce the rate of return on capital by the pharmaceutical industry by four percentage points. In 1984, the government cut the amount of money allowed to promote drugs from 10% to 9% of sales, and said they would treat the balance as extra profit which would be recovered through further reductions in prices. In 1985 legislation came into force which restricted the ability of G.Ps. to prescribe certain branded drugs, and forced generic substitution in these cases. The industry claimed that this resulted in job losses and redirection of capital investment to the tune of £138 million (ABPI, 1985, p. 9).

In 1986, the Pharmaceutical Price Regulation Scheme (PPRS) operated by the Department of Health which negotiates with the industry, increased the maximum return on capital allowed from 17.0% to 18.5%. It proposed a further increase for the following year. In addition, it maintained the global promotional expenditure figure at 9% of sales to the NHS with a fixed element of £400,000 to be allowed to each company, plus a fixed percentage of 6% of sales and a variable element determined by product range. Additional allowances are available during the first two years of a major new product launch.

In 1986 there were around 32,000 UK G.Ps. who wrote out almost 400 million prescriptions. On average, each G.P. was responsible for spending around £60,000 on drugs. Given the economic and political significance of the industry it is surprising that so little is understood about the way that

doctors prescribe. The minimal prior research in the area is reviewed in Sections 2.4 and 2.7 below.

### **2.3 Description of the Data Collection Method**

#### **2.3a Sampling**

The data was part of the JIGSAW database, a commercially operated panel of G.Ps. which was established by ISIS Research in 1985. The panel members are randomly selected in a two stage process.

The panel operator uses a computerised list of all G.Ps. in the U.K., with surgery addresses and telephone numbers. The list is updated on a six-monthly basis. The doctors are arranged into some 640 geographic 'bricks' with around 50 G.Ps. per brick.

50 bricks were randomly selected as sampling points, with the probability of selection being proportional to the number of doctors in each brick.

Each brick was then used to randomly generate two lists of eight doctors, a priority list and a reserve list. The reserve list was used in case a doctor on the priority list refused to co-operate. Thus if the fourth name on the priority list declined to join the panel, then the fourth doctor on the reserve list was approached. In this way the interviewer had no influence on recruitment.

An analysis of the panel members used in this research reveals a close match with the total population in terms of the number of doctors in the practice (where the mean absolute deviation between the panel and the population is under 3 percentage points), and the geographic spread based on Health Authority Regions (where the mean absolute deviation is less than 1 percentage point). See tables 2.1 and 2.2.

**Table 2.1 Number of Doctors in the Practice**

Number	<u>Proportion of Practices with N doctor in the practice:</u>		
	Population %	Panel %	Deviation
1	12	11	-1
2	15	14	-1
3	20	25	+5
4	18	21	+3
5	16	13	-3
6+	19	15	-4
Mean Absolute Deviation			3

**Table 2.2 Geographic Spread of G.P.s.**

Area	<u>Proportion of G.P.s. in:</u>		
	Population %	Panel %	Deviation
Scotland	11	10	-1
W Midlands	9	10	+1
Trent	8	6	-2
NW Thames	7	8	+1
N Western	7	6	-1
Yorkshire	6	8	+2
NE Thames	6	6	0
SE Thames	6	6	0
S Western	6	6	0
Northern	5	6	+1
SW Thames	5	6	+1
Wales	5	4	-1
Wessex	5	4	-1
Oxford	4	6	+2
Mersey	4	4	0
East Anglia	3	4	+1
Mean Absolute Deviation			1

**2.3b What the Panel Measures**

A 'good' sample (as available in this case) is only part of the process of extracting reliable data. In addition, the task is to ensure that the panel results in 'good'

ie reliable measures of behaviour (Sudman and Ferber 1979). In this instance the panel members report all new or changes of prescription for four therapeutic areas. This factor is important as it results in an unusual definition of market share, where repeat prescriptions are excluded. This issue is considered further in **Section 2.7** below. From the perspective of data integrity, this market definition helps confidence as the task is limited, thus reducing the potential for reporting fatigue and error. During the time covered by the current research, each panel member was paid £200 per year as compensation for their efforts. Each week the doctor sends a completed diary form to the panel operator, where the data is entered onto the JIGSAW computer database.

ISIS research claims a 10% annual attrition rate, which would indicate that the effort reward bargain is appropriate. New doctors are recruited to replace the irregular reporters. This attrition rate compares well with that experienced by AGB in grocery panels (Ellis 1989, p. 30).

The panel collects two other types of data. The first records demographic data about the members and is used in this research to explore whether variables such as age, sex or ethnic origin result in different prescribing patterns. The second type, which records promotional contacts between the doctor and drug companies was not used in this thesis for two reasons. Firstly, the panel operator indicated that it had been unable to find any consistent relationship between promotional contacts and actual prescribing behaviour (despite much encouragement from clients). Secondly, given the descriptive nature of the current research, consideration of exogenous variables was not appropriate at this (initial) phase.

#### 2.4 Description of the Data

For the purposes of this research, continuous reporters were defined as those who returned completed forms for 46 out of 52 consecutive weeks to the end of November 1986. Applying this constraint seemed sensible for the following reasons:

- No assumptions would be required about similarities in behaviour between the replaced and the replacement panel member.
- Given the recency of panel establishment some doctors might have forgotten to complete or send in the form on occasions, and therefore including these reporters would under-estimate the actual rates of prescribing.

The data donated by the panel operator consisted of three files, two of which contained prescribing data relating to two different product fields. The third file provided demographic data describing the panel members.

The resulting sample consisted of 243 G.Ps. representing some 0.8% of the population. Table 2.3 shows the match between the panel and the G.P. population of England, Scotland and Wales.

**Table 2.3 Comparison of the Panel with the Population**

1986	Population	Panel
Number of G.Ps.	31855	243
Male (%)	79	85
Female (%)	21	15
Born UK (%)	79	75
Born Elsewhere (%)	21	25
Under 45 years old (%)	55	48
45 or more years old (%)	45	52
Dispensing Practice (%)	12	13
Non-Dispenser (%)	88	87

Sources of Data: CSO, Welsh Office, Scottish Office

The sample used does therefore have a slight under-representation of women doctors, and appears to have an under-representation of doctors born in the UK. This latter point is not clear cut as the official statistics refer to location of birth, and the panel demographics record ethnic origin.

The discrepancy in the age profile is the largest (but only by 7%), and here again the definitions are different. The official statistics record the doctor's age, whereas the panel records the year qualified. This research assumes that the panel member was 25 when he or she qualified as a doctor. There were 21 members of the panel who qualified in 1966, and were therefore classified in the range 45 or above. If these were all under 25 when they qualified they would have been classified in the other category, and the panel would match the age profile of the population closely.

Overall then, the panel composition adequately reflects the population, and allows the examination of prescribing behaviour according to demographic variables.

The data on each product field comprised the doctor identifier, the week and the day that the prescription was written, the diagnosis made and the drug prescribed.

The final data (summarised in table 2.4) used in the main analyses were edited to exclude the two weeks around Christmas and the New Year as these showed a marked decrease in prescriptions written. These two weeks were analysed separately in order to see whether the intrinsic patterns were different or merely a function of the lighter rates of prescribing (see Appendix 1).

The data used was raw data which had not been summarised or processed.

Table 2.4 shows the difference in average prescription frequency between the two product fields, and also the differences in frequency and penetration between the three musculo-skeletal diagnoses and the five diagnoses in the cardiovascular product field.

**Table 2.4 Summary of Panel Data Used in the Study**

1986 48 Weeks	Number of Records Analysed*	B%	W
All Musculo-Skeletal	50,000	100	200
"Other" Musculo-Skeletal	32,000	100	130
Rheumatoid Arthritis	15,000	100	60
Osteo-Arthritis	2,000	89	10
All Cardiovascular	15,000	100	60
Anti-Hypertensives	8,000	98	30
Angina	3,500	95	15
Heart Failure	2,500	84	12
Arrhythmia	750	66	5
"Other" Cardiovascular	700	65	5
B% is the proportion of doctors prescribing at least once during the 48 weeks.			
W is the average number of prescriptions per doctor.			

Note: The numbers in table 2.4 are rounded \*n=243 doctors

The implications of these differences are considered in **Section 3.2** below.

It is interesting to note that table 2.4 shows similar patterns to fmcg brands which have been the subject of prior studies (Ehrenberg 1988). For example the higher the product class penetration level, the higher the average number of prescriptions written per doctor, a similar pattern to Double Jeopardy (see **Section 1.9c**). Double Jeopardy patterns, however, apply to sets of items (like brands) which are similar, and here the size effect is observed across diagnoses which are quite different. A further point of note is that here, very high numbers for the proportion

of prescribers and their prescribing frequencies are observed (see Section 1.11d). To put these numbers in context, doctors write new or changed musculo-skeletal prescriptions 20 times more often than households purchase instant coffee during the course of a year.

The drawbacks with prior studies of drug prescribing can be classified into three areas: small sample sizes, short analysis periods and levels of analysis which do not allow investigation of prescribing of individual drugs.

Typical of the studies is that by Baumgard, Frank, Rees and Shearer (1984) which utilises one group practice of five G.P.s. and reports differences in costs between the doctors' prescribing over a period of a year. It also reports differences in cost between new and repeat prescriptions in 15 therapeutic areas. The researchers conclude that any differences in prescribing costs between the doctors could be explained by the different mix of patients seen. The study has two of the three problems (sample size and level of analysis) and the findings cannot be generalised to all doctors or to the way that individual products within a therapeutic area are prescribed.

Anand (1986) reported his own prescribing behaviour by logging new prescriptions written during five fortnights between July 1983 and May 1984. He concluded that during this process he saw more patients but wrote less prescriptions using a smaller number of drugs. One of the areas covered was analgesic/anti-inflammatory, which coincides with the musculo-skeletal product field studied here. His method of reporting does not take diagnosis into account, and does not allow easy analysis of the split between branded and generic prescriptions. It also suffers in that the data was not collected continuously, and, of course, a sample of one is highly unlikely to represent 'general practice'.

Flemming (1985) analysed the prescription records of 11 G.Ps. during one week in 1980 and a further 23 during the following week. The main objective of this study was to research whether or not the act of self-auditing affected prescribing behaviour. The conclusion that it did not should provide further reassurance that the data examined in this research is representative of overall behaviour in this market. Flemming's data also allow some examination of prescribing rates of antibiotics and psychotropics, but again at an aggregate level of product class. This research therefore is not useful as a way of gaining an understanding of how doctors, in general, prescribe specific drugs in specific situations.

Van Zwanenberg, Grant and Gregory (1987) examined the prescribing behaviour of 12 practitioners in the Newcastle upon Tyne area. The focus was on the total number of prescriptions written, the number of antibiotic prescriptions written and the proportion of generic prescribing. The study concluded that the rates of generic prescribing rose significantly following an educational intervention devoted to 'rational prescribing'. The data was collected during 1985 and based on 150 consultations per practitioner. This research suffers from all three of the problems identified above.

Mills, Steele and Irwin (1988) used two practices to study repeat prescribing of non-steroidal anti-inflammatory drugs over an 18 month period. This was in order to monitor a policy of generic prescribing which the practices had implemented, and it showed variation in the increased rates of generic prescribing across practices. The research suffers from the sample size issue, but presents a further problem in that it recorded the results for the whole practice, which in one case was four full-time principals and one part-timer, and in the other, five full-time principals. Thus it is not possible to examine the behaviour of individual G.Ps. from this study.

In contrast to these prior studies, the current research is based upon 243 doctors' prescribing behaviour which is individually recorded on a weekly basis for a year. The data shows the name of the preparation written by the doctor along with the diagnosis (see Section 1.11a), and this enables the analysis of prescribing behaviour in a general way.

## 2.5 Rationale for Product Class Choice

The major influence was the constraint imposed by the panel which collects data on just four therapeutic areas, Musculo-skeletal and Cardiovasculars, which are covered in this research and Gastro-intestinals and Psychotropics which are not. The first three of these invite the doctor to record the diagnosis made, the fourth does not.

### 2.5a Desirable Characteristics of the Data

The first criterion was that there should be two therapeutic areas so that comparisons could be made to see if tentative generalisation would be possible.

The second criterion was that there should be more than one diagnostic choice for the doctor. This would maximise the opportunity to gain new knowledge about prescribing the same or similar products for different uses.

The third criterion was to include one therapeutic area which was concerned with serious long-term (chronic) disease. It was hypothesised that if a significantly superior drug existed to combat such a condition, then one would expect to see loyalty amongst its users.

The fourth criterion was to select a therapeutic area which contained both chronic and short term (acute) diagnoses. This would permit examination of prescribing patterns for different medical management strategies.

The fifth criterion was to select one therapeutic area which would exhibit seasonality in order to compare the patterns with the base case.

The sixth criterion was to use a therapeutic area which provided the doctor with the opportunity to prescribe multiple products for the patient. In this case it would be possible to examine whether pharmaceutical companies which satisfied all these prescribing needs benefited relative to those which selectively satisfied such needs. In this way it was hoped to explore aspects such as segmentation, and the implications for marketing management.

A seventh criterion was to provide an opportunity to study the differences (if any) between the way that branded items and their generic equivalents were prescribed. This ties in closely with the final criterion which was the potential to investigate the impact of legislation on prescribing behaviour. In 1986 the government banned the dispensing of certain drugs in branded form, only permitting the generic equivalent to be used for National Health Service dispensed prescriptions.

#### 2.5b Therapeutic Area Characteristics

The overriding criterion for selecting the diagnosis categories for the research was to maximise the output with a realistic workload, and extending the analysis to all four categories would have been too time consuming.

The therapeutic area encompassing depression was eliminated from the choice as there were no diagnosis options.

The gastro-intestinal therapeutic area was eliminated as it was not considered to be a seasonal condition, and

had fewer diagnostic alternatives than the cardiovascular field.

The cardiovascular therapy area was selected for inclusion because there were five diagnosis options. It also satisfied the third criterion above, with hypertension, angina and arrhythmia all being chronic, life threatening conditions. Cardiovasculars also satisfy the sixth criterion above. There are, for example, indications where two different products are prescribed to combat hypertension, with the patient receiving a beta blocker together with a diuretic. This means that the inclusion of this therapy area should allow the investigation of duplication of prescription between products from these two areas.

The musculo-skeletal product class provided three diagnostic categories. Osteo-arthritis and rheumatoid arthritis are chronic conditions, and the remaining 'other' category would, in general, comprise acute conditions, arising from aches and pains. It therefore satisfied the fourth criterion listed above.

It was (incorrectly) hypothesised that musculo-skeletal complaints would be more frequent during the winter months, whereas heart ailments would not depend upon the season (see **Section 2.6b**). The two categories therefore potentially allowed investigation of seasonality (see **Section 2.6** below).

Both therapeutic areas provide opportunities for studying the differences in the way that brands and generic equivalents are prescribed. In both cases the doctors can prescribe either the generic name or the brand name with differing consequences. If the brand is prescribed, then that is what the pharmacist must dispense. If the doctor writes the generic name on the prescription form then the patient will receive the

branded equivalent, as long as the chemical entity is still protected by patent. If the entity is out of patent, then the pharmacist is free to prescribe any of the available preparations which are chemically equivalent. Products used for musculo-skeletal problems can be categorised into two classes: analgesics and non-steroidal anti-inflammatories (NSAIDs). Legislation in 1985 affected analgesics, but not NSAIDs, and therefore the therapy area had the potential to offer insight into the impact of the legislation.

With hindsight, the research would have been enhanced by analysing all four therapeutic areas in order to see whether or not the patterns identified generalise further. At the time of negotiating access to the data it seemed that obtaining two of the four was a probability, but that the complete data set would not have been provided.

Nevertheless, the selection of the two categories appeared to satisfy all the research criteria, and promised a rich source for analysis.

Further research could look at the other two therapeutic areas and confirm or refute the conclusions of this study.

## **2.6 Stationarity and Seasonality**

The NBD and Dirichlet models referred to in Chapter 1 are capable of predicting buyer behaviour in markets where there is no trend in sales. They can model some (but not all) of the trends where major changes in the market occur, but given that most markets are approximately stationary, the models have found wide applicability.

Where changes in the market do occur, for example in the Christmas period for drug prescribing here, the Dirichlet

can still be used to model behaviour during the period in isolation (see Appendix 1).

Further, the use of the models to provide predictive norms allow measurement of the effects of marketing activities designed to cause a particular sales trend.

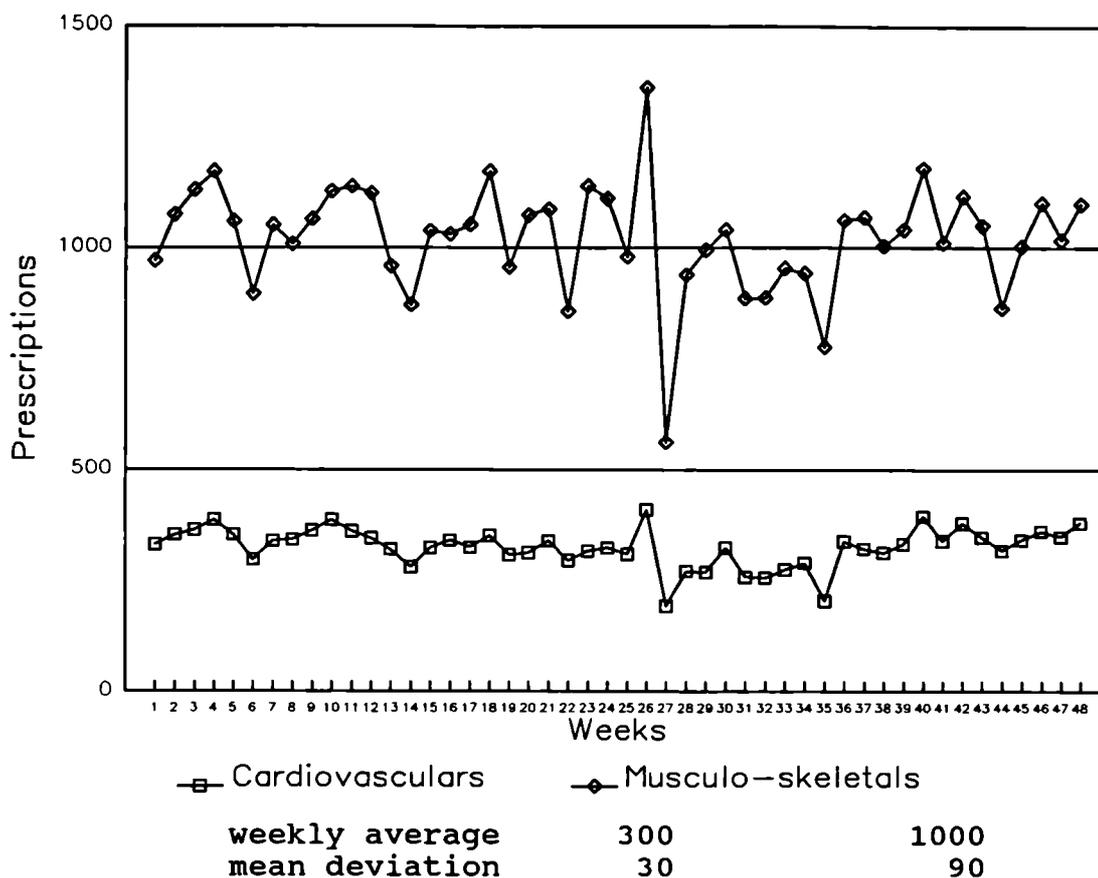
### 2.6a Stationarity

In Chapter 6 where the Dirichlet model is used to predict prescribing behaviour, the success of the model is measured by comparing its predictions with actual prescribing behaviour. This means that stationarity in the prescribing of drugs is assumed. Figures 2.1, 2.2 and 2.3 show the total number of prescriptions written in both product fields each week, month and quarter.

Looking at the weekly data, it is clear that the variability that does exist is consistent across both product fields. For cardiovasculars, the average number of weekly prescriptions was 300 and the mean deviation was about 30. For musculo-skeletal, the weekly average was about 1000 with a mean deviation of 90. In both cases there is a sharp rise in the number of prescriptions written in week 26 and a subsequent drop in week 27. This coincides with the peak summer holiday period and the rise in week 26 might indicate visits to the doctor brought forward by a week.

The aggregated picture provided by the monthly data adds support to this explanation and led to the inclusion of these two atypical weeks in the analysis, as these data points would not be used for predictive purposes. The graph showing the quarterly picture shows a relatively small but consistent drop in prescribing rates for the second and third quarters.

**Figure 2.1 Prescriptions Written per Week**



**Figure 2.2 Prescriptions Written per Month**

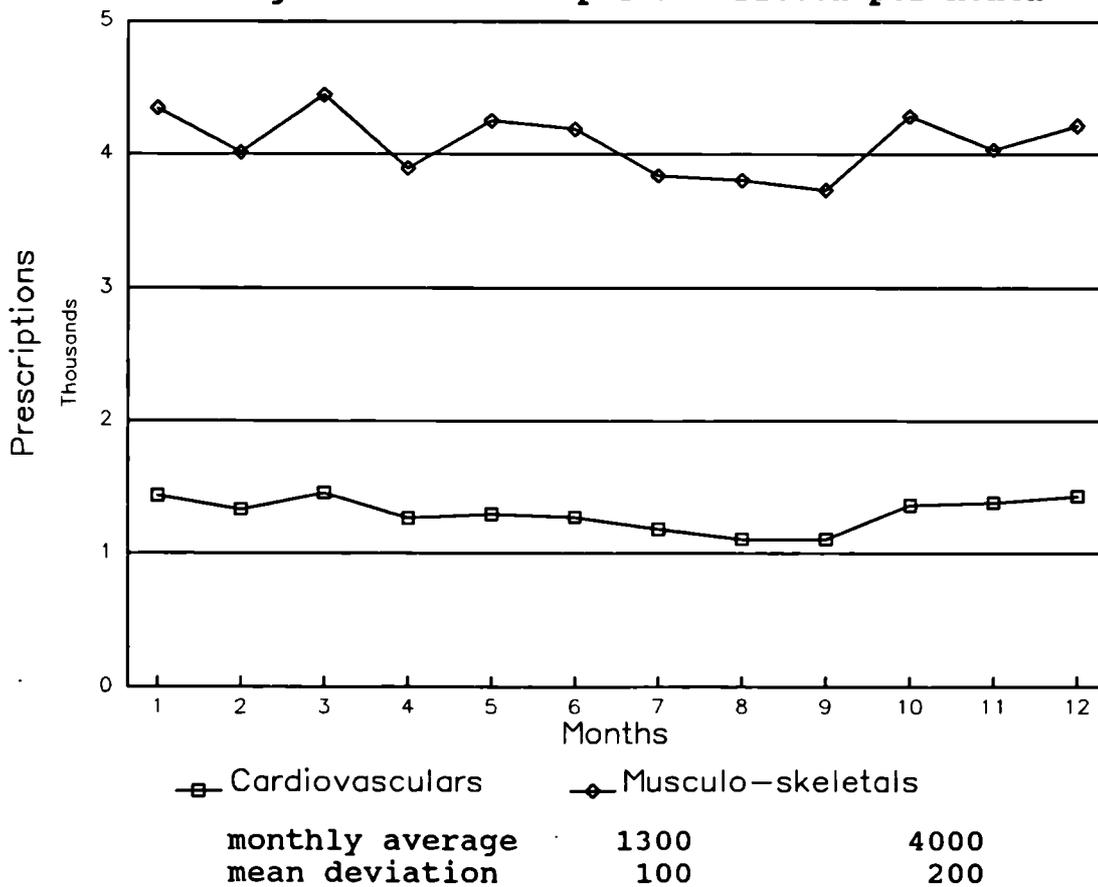


Figure 2.3 Prescriptions Written per Quarter

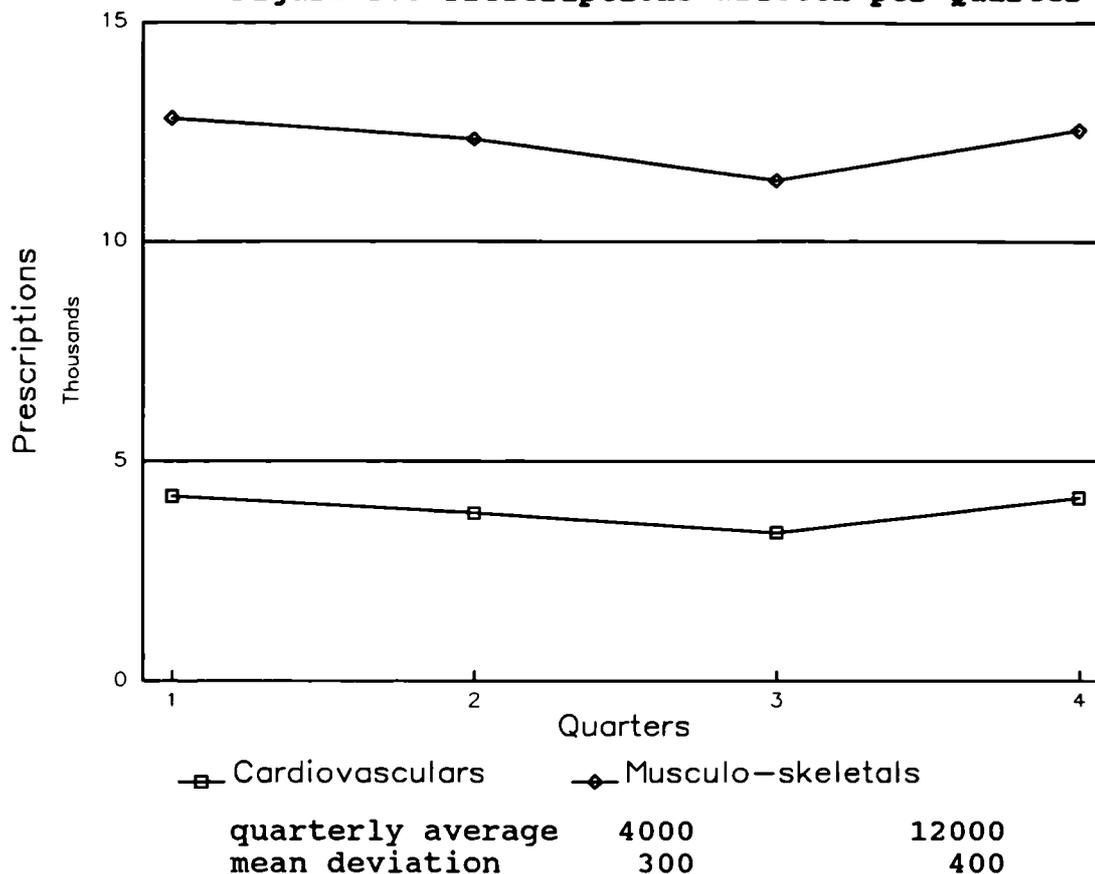


Table 2.5 shows the summary statistics for both product fields, and this together with a visual inspection of the graphs above show that the data is approximately stationary, and that there is no major deviation which is likely to mitigate against the use of a model such as the Dirichlet.

Table 2.6 shows the number of prescriptions written each quarter for each diagnostic sub-class. These data show similar patterns to the product classes in terms of stationarity.

Table 2.5 Summary Statistics of Prescribing

Number of scripts in:	aver. week	mean dev.	aver. mth.	mean dev.	aver. qtr.	mean dev.
Cardiovascular	300	30	1,300	100	4,000	300
Musculo-skeletal	1,000	90	4,000	200	12,000	400

nb. Numbers rounded for clarity

Here again the third quarter rates are in general lower than the average, but the degree of variation is not large enough to reject the use of a stationary approximation.

### 2.6b Seasonality

One of the most frequent explanations of non-stationarity is seasonal variation in demand. Examples would include the summer peak season for ice-cream or the winter increase for soup in grocery markets. If these seasonal variations are predictable, then it is possible to use models such as the Dirichlet to better understand the nature of the seasonal variation (see for example Wellan 1985; Ehrenberg 1988; Morrison & Schmittlein 1988).

In the case of the prescribing data, quarter 1 coincides with winter, quarter 2 with spring and so on. Looking at the data in table 2.6, it seems possible that there is a seasonal pattern in all the diagnostic sub-categories with the winter and autumn quarters seeing higher prescribing than the spring and summer quarters. One would have to observe these patterns over repeated years in order to establish whether or not there are real seasonal effects in this market. In the case of rheumatoid arthritis there appears to be no significant seasonal difference, and in all cases these trends are relatively small and will not hinder analysis.

Interestingly, the prior hypothesis regarding seasonality was not borne out with both product fields showing similar patterns, but this does enhance the potential to compare the patterns of cardiovascular and musculo-skeletal prescribing.

**Table 2.6 Prescriptions Written for Each Diagnosis  
(by quarter, Q)**

<u>Cardiovascular</u>	Q1	Q2	Q3	Q4	Average
<b>Total</b>	4,200	3,800	3,400	4,200	3,900
Anti-Hypertens.	2,100	2,100	1,700	2,200	2,000
Anti-Angina	1,000	800	800	900	900
Heart Failure	700	600	550	600	600
Anti-Arrythmia	200	150	200	200	200
Other	190	180	170	180	180
<u>Musculo-skeletals</u>					
<b>Total</b>	12,800	12,300	11,400	12,500	12,300
Other	8,500	8,000	7,500	8,000	8,000
Rheum. Arthritis	3,500	4,000	3,500	4 000	3,750
Osteo-Arthritis	500	500	400	500	500

nb. numbers rounded for clarity

### **2.7 The Market Definition**

A first consideration of market definition derives from the structure of the diary form filled in by the panel member. The form is designed to reflect diagnoses that the G.P. may make, and presumably product-markets of interest to the industry. This means that the definitions are not exhaustive and do not directly coincide with the therapeutic categories listed in the Monthly Index of Medical Specialities (MIMS), widely regarded as the prescribing 'bible'. Furthermore, the definitions in MIMS can themselves change through time. Table 2.7 compares the diagnosis options presented to panel members with those in MIMS (Nov. 1985 & Jan. 1988).

The difference in definition does not render the data any less valid, and the degree of overlap is significant in any case. Here the difference is merely documented.

A more significant issue derives from the fact that the data base used limits analysis to a part of the market which consists solely of new and changes of prescription, and it therefore omits repeat prescriptions for chronic conditions such as heart disease and osteo-arthritis. One approach to

dealing with this problem is to assume that doctors are less likely to exhibit different behaviours when they prescribe for new and repeat chronic disorders than they are when prescribing for new chronic and new acute disorders. It can be further assumed that the 'Other' diagnostic sub-category of the musculo-skeletal product class is largely comprised of prescriptions written for non-recurring aches and pains. Thus, if similar patterns are found across all the diagnostic sub-categories studied here then we have some grounds for tentatively predicting similar patterns for the repeat prescription part of the market. If, however, repeat prescribing is different, then the exclusion of repeat prescriptions may mean that this research does not reflect prescribing behaviour in a significant proportion of the market.

This proposition was checked in a crude way by comparing the panel market shares for the top products in both product fields with those from another commercial market research source (IMS). The results showed close agreement with the average variation across 50 brands being less than 2 share points.

An alternative approach is to investigate the proportion of prescriptions which are new and which are repeat. Here again the literature proved to be of limited use with the following exceptions.

Baumgard et al. (1984) showed that in a practice consisting of four principles and a trainee, 51% of prescriptions written during a year were new with the balance classified as repeats. However, as repeat prescriptions tended to cover a longer treatment period than new prescriptions, the latter

Table 2.7 Comparison of Prescribing Usage

	Panel	MIMS 1985	MIMS 1988
<b>Cardio-vascular</b>			
1	Anti-Hypertensives	Arrythmias, shock, and cardiac failure	Arrythmias and cardiac failure
2	Anti-Angina	Angina and Ischaemic heart disease	Anti-Angina
3	Heart Failure	Peripheral vasodilators and cerebral activators	Diuretics
4	Anti-arrythmia	Anti-hyper-tensives	Anti-hyper-tensives
5	Other	Migraine	Circulatory disorders
6		Anticoagulants, antithrombotics and fibrinolytics	
7		Haemostatics	
8		Hypolipidaemics	
<b>Musculo-skeletal</b>			
1	Rheumatoid Arthritis	Non-steroid-anti-inflammatory drugs	
2	Osteo Arthritis	Gout	
3	Other	Muscle relaxants	
4		Embrocations	
5		Neuromuscular drugs	

accounted for a lower value share. Their research showed that in the case of cardiovascular drugs new prescriptions accounted for 44% of the total. In the case of musculo-

skeletals the figure was 36%. Despite the small sample size, the findings are not too different from research by Bradley and McCourt (1986) who found that 48% of NSAID prescriptions were new.

The limited evidence does, therefore, indicate that the current research is studying prescriptions which account for more than 10% (by value) of the entire UK market worth some £200m at 1986 prices.

If there are significant differences in the way that doctors prescribe for repeat, as opposed to the 'new' situations described in this study, then it would not be possible to generalise these findings further. However, two important points should be considered. Firstly, there is no reason to suppose that the patterns of repeat prescription will vary across brands. Secondly, the norms that are reported here could be used to evaluate how repeat prescribing behaviour differs as and when the data become available.

It is predicted that repeat prescribing should exhibit broadly similar patterns for the following reasons: Firstly, market shares representing all prescriptions are similar to those for 'new' prescriptions only, and as the Dirichlet model's main input is market share, it is unlikely that grossly differing patterns would be seen by merely examining repeat prescribing on its own. Secondly, the patterns here are consistent with many prior studies where the buyer is repeat purchasing from product fields for the same consumption unit, a situation like repeat prescribing.

One reason why this data base may be more useful is that repeat prescribing is akin to varying the quantity purchased on a shopping trip. A new prescription written today with the prospect of nineteen repeats is "equivalent" to prescribing 20 units today, and so new and changes of prescription more accurately represent the purchase occasion which is the normal unit of analysis for NBD-Dirichlet

modelling (Ehrenberg 1988). In addition, the fact that the patterns for new prescribing are so familiar, and yet the situation so different leads to the conclusion that radically different behaviour for repeat prescribing would be surprising.

Two further points are worth considering in estimating the relevance of the data used. Firstly, by recording only new and changes of prescription, and ignoring the current repeats, the data represents a forecast of the total product/market at some point in the future. This representation has direct relevance to marketing practitioners in terms of strategy and tactics. Secondly, the examination of patterns of behaviour devoted solely to new and changes of prescribing is intrinsically interesting. In some ways it mirrors a situation where a buyer is faced with a new decision or where there is an element of dissatisfaction with a prior choice. Thus it becomes feasible to test hypotheses about how such markets work and how if at all they differ from the more traditional f.m.c.g product markets.

### 2.8 Summary

This chapter has looked at the economic significance of the pharmaceutical market and shown also that the specific part examined by this thesis was worth around £200m in 1986.

It has described and justified the use of the prescription data which the thesis analyses and also reviewed relevant research, all of which was carried out by medical practitioners and researchers.

The chapter also established the stationary nature of the data and considered the issues of seasonality and market definition in the context of the current research.

**PART II - DESCRIBING AND MODELLING THE DATA**

**CHAPTER 3 - HOW DOCTORS PRESCRIBE THE TWO PRODUCT CLASSES**

**CHAPTER 4 - DESCRIPTIVE DATA PATTERNS**

**CHAPTER 5- THE DIRICHLET MODEL**

**CHAPTER 6 THE FIT OF THE NBD-DIRICHLET AT  
THE PRODUCT CLASS LEVEL**

## **CHAPTER 3: HOW DOCTORS PRESCRIBE THE TWO PRODUCT CLASSES**

### **Overview**

#### **3.1 Introduction**

#### **3.2 Aggregate Homogeneity - Individual Heterogeneity (Both Product Fields Combined)**

#### **3.3 Aggregate Homogeneity - Individual Heterogeneity at the Product Field Level**

3.3a Comparing the two Product Classes

3.3b Comparing within Product Classes

3.3c Implications of Individual Heterogeneity

#### **3.4 Aggregate Homogeneity - Individual Heterogeneity at the Diagnosis Level**

#### **3.5 Comparing how Brands and Generics are Prescribed at the Aggregate Level**

#### **3.6 Comparing Prescribing Behaviour of Different Demographic Sub-Groups**

#### **3.7 Differences due to Demographics and Diagnosis**

#### **3.8 The Relationship between the Number of Prescriptions Written and the Brand Portfolio**

3.8a Contingency Table Analysis

3.8b Regression Analysis

3.8c Data Reduction

#### **3.9 Similarities and Differences Between Prior Studies**

3.9a Heterogeneity

3.9b The Buyer

3.9c Non-Buyers versus Infrequent Buyers

#### **3.10 Summary**

### Overview

This chapter describes the key patterns of prescribing at the diagnosis and product class level, before examining individual entities in the rest of the thesis. The chapter provides some insights which are consistent with prior knowledge, and others which are new. The main findings of this chapter are summarised below.

- There is very little variability in the aggregate measures of prescribing when comparing time periods of the same length.
- The number of prescriptions written by individual doctors is extremely varied - the heaviest prescribers prescribe 100 times more frequently than the lightest prescribers.
- The variance in the number of patients on the doctor's list does not account for the observed heterogeneity.
- The heterogeneity is observed at both the product class and the diagnosis levels.
- On average, there is no obvious difference in the way that doctors prescribe brands and their generic equivalents.
- There are no differences in the way that doctors categorised by various demographic variables prescribe for either product classes or diagnoses.
- Frequent prescribers tend to use more different drugs than infrequent prescribers, and a simple model is found to describe the relationship.

### 3.1 Introduction

In this chapter a number of prescribing patterns are explored at the aggregate product level, (consideration of individual brands will start in **Chapter 4**). **Section 3.2** examines the patterns of prescribing behaviour at the level of both cardiovasculars and musculo-skeletal combined and

highlights the extreme heterogeneity found in this market. **Section 3.3** repeats the analysis at the level of the two product fields.

**Section 3.4** looks at prescribing behaviour for each diagnosis to see whether or not this 'usage' factor influences the patterns in the data. **Section 3.5** compares the prescribing of brands with generics in terms of the proportion of doctors prescribing and their frequency of prescription. In keeping with the convention adopted throughout this thesis the term employed for a chemical name used by a doctor will be an "entity". This is to avoid using the term brand in an inappropriate way (for example when the generic name has been specified by a doctor). The analysis conducted provides a simple but effective test of whether branding results in higher levels of prescription frequency.

In **Section 3.6** the influence of demographic variables is explored to see whether or not a priori segmentation might be used to more effectively target resources and hence increase an individual entity's sales. **Section 3.7** completes the picture by combining demographic variables with the eight different diagnoses to see whether any obvious relationships exist.

**Section 3.8** examines the relationship between the number of prescriptions written and the size of the portfolio used by doctors and **Section 3.9** provides a comparison between some previously reported studies and this one to highlight areas of difference. The chapter concludes with a summary.

**Chapter 4** will look at these and other patterns at a more detailed level of analysis focussed upon individual brands and generics.

**3.2 Aggregate Homogeneity - Individual Heterogeneity,  
(Both product fields analysed together).**

The aggregate homogeneity of the market may be simply described by looking at the data for the proportion of doctors prescribing at all during each week together with the average number of prescriptions written per prescribing doctor. Table 3.1 shows that throughout the year about 80% of doctors will write 7 new or changes of prescription (for both product fields combined) each week, and that these figures do not change dramatically from week to week.

**Table 3.1 The Proportion of Doctors Prescribing and their Frequency of Prescribing.**

(48 weeks)	Average	Mean Deviation
Proportion of Prescribers (%)	82.0	6.0
Weekly prescription Frequency	6.8	0.4

This aggregate stationarity does mask very large variations in individual prescribing behaviour, manifested in differences in overall frequency of prescribing as well as the number of different drugs used.

The individual variation can be seen across different time periods. Table 3.2 lists the number of prescriptions and the number of brands used by a fairly typical selection of 8 doctors who represent light, medium and heavy prescribers across two six monthly periods. The table also shows the total number of brands used in the year and the final column shows the percentage of all the brands used in common during the two half year periods.

Doctor H wrote 9 prescriptions using 8 different entity names during the year. In each six month period this doctor used four entities and never used the same one in both periods. Doctor H (who was the lightest prescriber) may be contrasted with Doctor A who was one of the heaviest

prescribers writing almost 1000 prescriptions in the year. As a frequent prescriber, Doctor A had already used most of the available entities during the first half of the year, and therefore two thirds of the portfolio was utilised in both periods.

**Table 3.2 Prescribing Behaviour of 8 Doctors over two half yearly periods**

Doc	<u>Prescriptions</u>		<u>Number of brands</u>		<u>No. of Brands</u> year	<u>Common Brands</u> %
	1st half	2nd half	1st half	2nd half		
A	436	483	50	55	63	65%
B	364	450	48	56	65	60%
C	392	332	38	41	52	50%
D	122	115	19	18	24	50%
E	104	130	20	23	31	40%
F	10	11	9	6	13	15%
G	8	11	4	6	9	10%
H	4	5	4	4	8	0%
.						
.						
.						
Average	180	190	24	26	33	36%
Average (243 docs)	137	130	27	26	35	50%

On average then, doctors write about the same number of prescriptions in each half year, and they use about the same number of drugs to fill those prescriptions. By and large, however, the individual doctors tend to use different drugs half of the time.

Looking at the annual data we find that the average number of new prescriptions written was about 250 with a range of 10 to 1000. The average number of names used in the year was 35, representing one third of the available prescription items. Here, the smallest number of entities utilised in prescribing was 8 and the largest number 65 per doctor.

The wide variability in the behaviour of individual doctors where the rate of prescribing varies by as much as one hundred fold is an important finding in its own right. There are certainly no published studies which record this degree of individual heterogeneity, and so some examination of the phenomenon is appropriate. In Section 6.2 the heterogeneity of the two separate product fields is modelled using the already well established negative binomial distribution (NBD).

A potentially simple explanation for this heterogeneity would be different patient list sizes causing different rates of prescribing, but table 3.3 shows that this is not the case.

**Table 3.3 Prescriptions Written in Practices of Different Size (both product fields combined).**

1 year Practice Size	%of doctors	Average No. of Scripts	Mean Deviation	Minimum	Maximum
>10000	25	290	120	10	1000
5000-10000	40	270	110	20	800
<5000	35	235	100	20	900
All	100	260	110	10	1000

Here summary statistics on the number of prescriptions written are shown for the population and three different sizes of practice.

It is clear that as the number of patients diminishes the rate of prescribing also drops but less than proportionately to the drop in practice size. This effect and its direction is unsurprising, but the small size of the effect is of interest and shows that the variability in individual behaviour is greater within, than between each category of practice size.

The implication for pharmaceutical marketers is that targeting doctors who are in large practices may result in reaching slightly 'heavier' prescribers. There will nevertheless be other doctors who are equally 'heavy' prescribers in medium and small size practices, (which account for three quarters of all practices) and that a targeted approach would exclude them.

The pattern for the number of entities used by the doctors in the panel is even flatter than that for the number of prescriptions written. Table 3.4 shows that the average number of entities prescribed in a year is independent of the number of patients on the practice list.

**Table 3.4 Entities Used in Practices of Different Size (both product fields combined).**

1 year Practice Size	%of doctors	Average No. of Entities	Mean Deviation	Minimum	Maximum
>10000	25	35	12	7	63
5000-10000	40	36	8	8	65
<5000	35	35	10	9	63
All	100	35	10	7	65

The data in table 3.4 are intuitively appealing. There is no reason to expect doctors to rely on a differing portfolio size, unless large practices resulted in those doctors seeing rare conditions which would require drugs not in the 'standard portfolio'.

Prior studies in the buyer behaviour field have shown that family size is a minor factor when considering heterogeneity in terms of the buying unit, but it is hard to think of simple reasons to explain why one doctor would use 20 different prescription names in a year and another would use twice this number.

It can be seen in Section 3.6 below that other descriptive variables fail to account for this pattern and further research of a qualitative nature would be a route for attempting to understand the reasons for this extreme form of heterogeneity.

### 3.3 Aggregate Homogeneity - Individual Heterogeneity at the Product Field Level.

The stationarity of both product fields was demonstrated in Section 2.6, and the variation in behaviour of individual doctors was illustrated in Section 3.2. The prescribing behaviour in both product fields is now summarised, and then the variability across the two fields is considered.

#### 3.3a Comparing the Two Product Classes

Table 3.5 shows that although the average number of prescriptions written and the average number of entities used does not change from one half year to the next, there is a wide variation in the behaviour of the sample. Looking at the first column of table 3.5, the average number of prescriptions written for all cardiovascular diagnoses was about 30 during the first half of the year. The mean deviation from this average was 20 and the range of the prescription frequency was 1 to 150. The second column shows a similar pattern for the second half of the year. The third and fourth columns show the same data for the number of entities used in each half year, and again the pattern of high heterogeneity is evident. The fifth column shows the data for the number of entities used for the whole year in each product field and the final column shows the percentage of the annual portfolio which was used in both six monthly periods. Thus, for cardiovasculars, a doctor will on average, prescribe just under half of the entities used in the first six monthly period again in the second half of the year.

In the case of musculo-skeletals, about 50% of the entities used in the first half will be used again in the second.

Table 3.5 also shows that the main difference between the two product fields lies in the number of prescriptions written rather than the number of entities used. On average, doctors write three times as many prescriptions for musculo-skeletals than they do for cardiovasculars but they only employ a few extra entities to fulfil their increased prescribing requirements.

**Table 3.5 The Variability of Individual Prescribing for Cardiovasculars and Musculo-skeletals.**

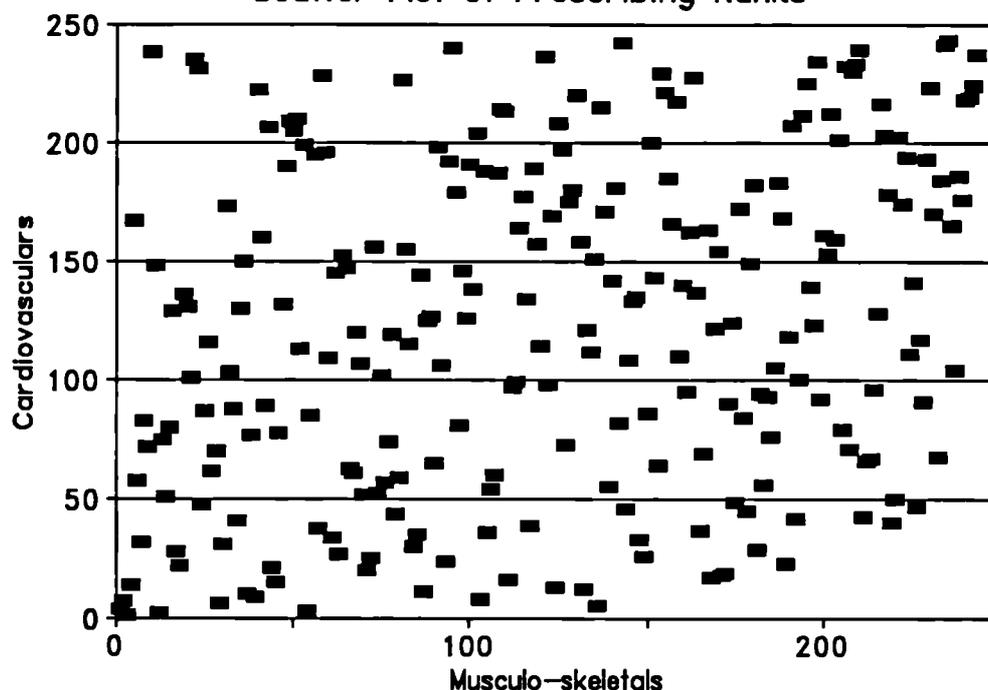
<u>CARDIO.</u>	<u>Prescriptions</u>		<u>No. of Brands</u>		<u>No. of Brands</u>	<u>Common Brands</u>
	first half	second half	first half	second half	year	%
Number	34	32	12	12	16	40%
Mean dev.	21	20	5	5	6	16
Minimum	1	1	1	1	1	0
Maximum	155	168	30	31	33	100
<u>MUSCULO.</u>						
Number	104	98	15	14	19	53%
Mean dev.	47	46	5	4	5	10
Minimum	2	1	1	1	2	0
Maximum	452	390	29	29	35	90

The table also shows that individual behaviour was far more varied in terms of the number of prescriptions as opposed to the number of entities, and this raised the question as to whether the prescription variability was consistent between the two product fields. A plot of the prescribing rank in each product field for each doctor is shown in figure 3.1 which indicates there is no strong tendency for prescribing weight in one product field to occur in the other. This was tested by

calculating the rank correlation based on the number of prescriptions written for the year.

The Spearman coefficient was just under 0.3 ( $p=0$ ) indicating that the rate of prescribing in one product field is not a good predictor of the rate in the other product field.

Figure 3.1  
Scatter Plot of Prescribing Ranks



A cross-tabulation of heavy, medium and light prescribers (defined as the top, middle and bottom third of prescribers) in both product fields is shown in table 3.6 and this confirms the weak relationship that exists.

These analyses raise the question of how different are the two product classes in terms of prescribing patterns. Table 3.7 shows the size and the annual prescription frequency for both product fields.

**Table 3.6 Cross-Tabulation of Prescribing Weight**

<u>Musculo- Skeletals</u>	<u>Cardiovasculars</u>		
	Heavy	Medium	Light
Heavy	48%	33%	20%
Medium	27%	36%	37%
Light	26%	33%	41%

**Table 3.7 Product Class: Size, and Prescription Frequency**

48 Weeks	Number of Prescriptions Written	Average Prescription Frequency (W)
Musculo- Skeletals	50,000	200
Cardio- Vasculars	15,000	60

In terms of new and changes of prescription, the musculo-skeletal market is three times as large as the cardiovascular. This difference in size does not show up in the number of prescribers but in the average frequency of prescription.

All doctors prescribe drugs at least once a year in both product fields but for musculo-skeletals, doctors write about 4 new or changes of prescription, on average, each week. In the other product field, prescription frequency is less at just over once a week, on average.

### 3.3b Comparing within Product Classes

The lack of correlation between prescribing weight across product classes led to an examination of the relationship across diagnoses within the product classes. Table 3.8 shows the Spearman coefficients for prescribing ranks between the diagnoses.

While all these correlation coefficients are 'statistically significant', the strength of the relationship in term of prescribing weight is, in some cases, even weaker than the one between the two product classes. This shows that a doctor's rate of prescribing in one diagnosis is not a good indicator of their behaviour in other situations.

**Table 3.8 Rank Correlations Between Diagnoses**

<u>Musculo-skeletals</u>	Other	Rheumatoid Arthritis		
"Other"				
Rheumatoid Arth.	.45			
Osteo-arthritis	.31	.15		
<u>Cardiovasculars</u>	Hyper.	Angina	Failure	Arryth
Hypertension				
Angina	.49			
Heart Failure	.48	.50		
Arrythmia	.35	.46	.48	
Other	.21	.19	.11	.24

### 3.3c Implications of Individual Heterogeneity

Both product fields have higher usage rates than most consumer products previously studied. Cardiovasculars are closer to the rates observed with petrol, and musculo-skeletals show higher rates more akin to cigarette purchase. A further way to conceptualise these product markets is to compare doctors with some fast moving consumer products at the retail level. It does seem clear that the number of entities used by doctors in a six month period is at least as large as the number of brands of a product class stocked by a large retail outlet. In addition, the 'turnover' of musculo-skeletal prescriptions is similar to that which will be found for some product classes within the store. This then extends the analogy between doctor and retail outlet proposed in **Section 1.11b**.

The extent of the heterogeneity in the two product fields shown in table 3.5 has already received comment in **Section 3.2**. One way to start to understand the variability in prescribing rates among doctors is to compare the distribution of prescription frequencies of individual entities within each product class. A second step is to see how closely an established theoretical model will fit the observed distributions. If the fit between observation and theory is good then one could conclude that the degree of buyer heterogeneity is linked in a predictable way to average prescribing frequency. This would not reveal reasons why the behaviours of individual doctors vary to such a great extent, but it would provide a theoretical basis for such variability. This analysis is conducted in **Section 4.4**

#### **3.4 Aggregate Homogeneity - Individual Heterogeneity at the Diagnosis Level.**

To examine the individual variability in greater detail, the prescriptions for patients with cardiac arrhythmia (which represents one of the diagnostic categories embedded within the cardiovascular product field) are analysed in Table 3.9. During the 48 week period, two thirds of the total sample prescribed at least once for this condition. The table shows the prescribing of 10 of these doctors in each of the two half-yearly periods as examples of the variations in behaviour.

The wide variation in prescription frequency is illustrated by Doctor 1 who prescribed a total of 30 times in the year, whereas doctors number 9 & 10 prescribed just four times for this particular diagnosis. Just over 30% did not prescribe at all.

None of the ten doctors prescribed the same combination of drugs the same number of times in both periods.

**Table 3.9 Prescribing of Anti-Arrhythmics  
(aggregated in half-yearly periods).**

Doctor	Number of prescriptions:		Whole Year
	First 6 Months	Second 6 Months	
1	3A+3B+1C+4D+5E	4A+9D+1E	30
2	2A+8C+1E	3A+6C	20
3	3A+3D	5A+2D+2E	15
4	2A+3C+1D+1E	1B+4C+1D+1E	14
5	4C+1D+1E	1A+3C+2E	12
6	5A+1C	2A+1D+2E	11
7	2A+1C	4A+1C+2E	10
8	1A	1A+2C+1E	5
9	2A	1C+1D	4
10	2A	2C	4
etc			
	116A	119A	235A
	78B	88B	164B
Total	45C	40C	85C
	34D	42D	76D
	109E	107E	216E
	382	396	778

Key: A-D represent the four largest product types used in this diagnosis, as follows:

G.P. wrote on prescription form:

A = **Lanoxin or Digoxin**. Digoxin is the generic name, but the patient would receive the branded version, Lanoxin.

B = **Inderal, Half Inderal or Inderal LA**. All are different formulations of branded Propranolol, produced by the same manufacturer (ICI).

C = **Propranolol**. Here the pharmacist could dispense any product which contained Propranolol. The resulting item could be one of five products (including Inderal), from five different manufacturers.

D = **Verapamil, Cordilox and Securon**. Verapamil is the generic name for Cordilox and Securon, so the patient could have received either of these three if the GP had written Verapamil, but where either Cordilox (20% of cases) or Securon (3% of cases) had been written, the patient would have received these specific preparations.

E = An aggregate of all the other entities used.

The reasons why doctors differ in their behaviour is discussed by Knox (1987), who suggests that practice demography and specialists' attitudes to regional morbidity patterns play an important role. In his research, Knox cites a practice with a high proportion of women of child bearing age as having a higher proportion of oral contraceptive prescriptions than an average practice. He also describes how the prescription rate of an anti-ulcer preparation was 'markedly low' in North-East Scotland when compared to East Scotland, where local specialist interest was high. Unfortunately, Knox does not provide a quantification of these effects.

The degree of heterogeneity in the current research data cannot be accounted for by such regional differences, and making a significant search for an explanation is outside the scope of this research. However, the ability to capture and describe this heterogeneity is a central objective of the current thesis and the data should be a good test of the types of model described in Chapter 1.

Despite individual variations, the total number of prescriptions written for each of the five entities in table 3.9 shows consistency in each of the two periods: About 110 prescriptions of A, about 80 of B and so on. The largest difference is to be found in entity D, and much is attributable to Doctor 1 who prescribed it nine times in the second half-year.

The patterns for each of the other diagnoses are similar and, like the product class comparisons (table 3.7), the main difference shows up in prescription frequency as shown in table 3.10.

In the case of two of the three musculo-skeletal diagnoses, a similar picture to that of the two product classes is seen. With rheumatoid-arthritis and other musculo-skeletal

**Table 3.10 Diagnosis: Size, Penetration and Prescription Frequency**

48 Weeks	Number of Prescriptions Written	Number of Doctors Prescribing	Average Prescription Frequency
			(W)
Other Musculo	32,000	240	130
Rheum. Arthr.	15,000	240	60
Osteo-Arthr.	2,000	215	10
(All Musc.-Skel.)	50,000	240	200
Hypertension	8,000	240	35
Angina	3,500	230	15
Heart Failure	2,500	200	12
Arrhythmia	800	160	5
Other Cardio	700	160	5
(All Cardio.)	15,000	240	60

Note: Data rounded for clarity

diagnoses, the variation is in their prescribing frequency, not the number of prescribers. As the size of the diagnosis category decreases, the differences start to show in the number of prescribers as well as the frequency of prescribing. Thus osteo-arthritis is a condition seen by fewer doctors and those doctors prescribe less frequently than they do for the other diagnoses.

This feature is repeated in the cardiovascular product field. The most common diagnosis, hypertension, is treated by more doctors who prescribe more frequently than in the case of a rarer diagnostic situation like arrhythmia.

The explanation for this pattern lies in the rarity of the diagnosis. If a condition affected one person in every ten thousand, there would be around 5000 sufferers in the UK. As there are about 32,000 G.P.s, most would not have the opportunity to see a patient or prescribe for the condition. Those who did see the condition would most likely see just one patient and would have just one opportunity to write a new prescription. In contrast, a common occurrence like

aches and pain from over-exertion in sport would probably be seen by virtually all G.Ps relatively frequently. Thus there would be more prescribers, each of whom had a greater opportunity to prescribe than in the case of the rare condition.

This proposition would imply that the practice size would correlate with prescribing for 'rare' diagnoses, and one would therefore expect the biggest practices to account for the largest proportion of prescriptions for 'rare' diagnoses. However, given the finding in Section 3.2 that practice size had a very small effect on prescribing compared to variation in individual doctor behaviour, one would expect to find little if any empirical support for the proposition. This is confirmed in table 3.11 below.

**Table 3.11 Share of Prescriptions by Rare Diagnosis and Size of Practice**

	Small (%)	Medium (%)	Large (%)
Heart Failure	27	42	31
Osteo Arthritis	34	42	24
Arrhythmia	29	39	32
Other Cardio.	36	44	20
Average	32	42	27
Average all Diagnoses	30	41	29

### **3.5 Comparing how Brands and Generics are Prescribed at the Aggregate Level.**

Branding is widely accepted as one route to superior profitability in marketing. Doyle (1989) defines a successful brand as:

'a name, symbol, design, or some combination, which identifies the "product" of a particular organisation as having a sustainable differential advantage.'

Doyle proceeds to the position that a brand is successful (ie big) because it is preferred by customers and the result

is higher share and profitability than other less successful brands. His analysis fails to account for the fact that there are many successful brands which are small in market share terms, and attract similar degrees of loyalty to large brands.

In the current research, the opportunity exists to compare the ways in which doctors prescribe brands with the generic alternatives.

In this instance the distinction between a brand and its generic equivalent lies in the name that the doctor uses when the prescription is written. As long as the drug is still 'in patent' then the pharmacist must dispense the branded version even if the doctor has specified the generic name. There will be other instances where the patent has lapsed but the pharmacist would still be obliged to dispense the brand (if that was what the doctor had specified). However, they could dispense either the brand or a generic equivalent if the doctor had specified the generic name on the prescription.

In any case, the patient receives a chemically identical formulation, and this contrasts with the parallel in consumer markets of choosing between a manufacturer's brand and a distributor's offering.

If the view of branding expressed by Doyle is correct, then one would expect to see brands with relatively high prescription shares when compared to their generic equivalents. This aspect will be explored in detail in **Chapter 4**, but here the aggregate pattern is examined, along with the sub-patterns for the different diagnoses in the cardiovascular product field.

Table 3.12 shows the summary prescribing statistics of the panel in terms of the major brands and generics used in the

five different diagnosis categories of the cardiovascular product field.

**Table 3.12 Cardiovascular Diagnosis & Product Type: Share, Number of Doctors and Prescription Frequency**

19 major brands and 5 largest generics only						
48 Weeks	Number of Prescriptions Written		Number of Doctors Prescribing		Average Prescription Frequency	
	B	G	B	G	B	G
Hypertension	3800	1300	225	175	17	7
Heart Failure	900	425	150	120	6	4
Angina	700	200	175	80	4	3
Other Cardio	300	50	100	40	3	1
Arrhythmia	175	30	80	20	2	2

**Key:** B = All 19 major brands  
G = All 5 major generics

One reading of table 3.12 shows support for the traditional view of branding. Brands are used by more doctors more frequently in all diagnosis categories than generics. However, traditional theory would lead one to conclude that if there were two product-markets of roughly equal size, one of which was exclusively served by brands and the other by generics, then one would expect that the consumer preference for brands would show not only through lack of buyer overlap but also through higher brand purchase frequencies.

This thesis will consider the overlap or duplication issue in **Chapters 4 and 8**, but it is extremely enlightening to compare the data on generics in the Angina diagnosis above with brands in the Arrhythmia category (ie two categories of similar size). This shows that there is no great difference in purchase frequency for brands and generics when the size of the category is taken into account. This point is made more strongly by re-presenting the data in table 3.12 as table 3.13.

**Table 3.13 Cardiovascular Diagnosis & Product Type:  
Relative Penetration and Prescription Frequency.**

(19 major brands and 5 largest generics only)		
48 Weeks	Relative Penetration (%)	Prescription Frequency (W)
B1	95	17.0
G1	88	7.4
B3	66	5.9
B2	70	4.2
G3	61	3.6
B5	42	2.9
G2	41	2.5
B4	33	2.1
G5	19	1.4
G4	11	1.6

Key: B1-B5 = All 19 major brands in each diagnosis  
G1-G5 = All 5 major generics in each diagnosis

Here, the number of doctors prescribing in each of the diagnoses is divided by the total number who prescribed brands or generics as appropriate. Thus out of the total of 243 panel members, 237 prescribed at least one of the 19 major brands at least once in the 48 weeks, and 200 prescribed at least one of the five generics during the time period. These ratios expressed as a percentage are termed the relative penetration.

In this table, the downward 'Double Jeopardy' type pattern is again evident, with the frequency of prescribing determined by the size of the unit of analysis and not dependent upon the form of the product being prescribed. One implication of this finding is that individual brands and generics should vary according to their market shares alone in terms of penetrations and frequencies, and that brands should not attract higher levels of repeat prescribing or loyalty than their generic equivalents. This will be examined in Chapter 8.

### 3.6 Comparing Prescribing Behaviour of Different Demographic Sub-Groups

There has been some research which claims to find relationships between propensity to prescribe and type of doctor classified by their demographics. For example, Maier and Saunders, (1990) determined segments based upon variables including the age and sex of the doctor, concluding that they would respond differently to the same marketing programme, and that targeting would therefore lead to better resource allocation. Maier and Saunder's study relied on attitudinal data and in the case of the current research it is possible to examine the impact of demographic variables on actual behaviour. Table 3.14 shows how the total number of prescriptions written in the musculo-skeletal product class breaks down into the number of prescribers and prescription frequency. The variation by demographic sub-groups is also presented.

Looking at the patterns exhibited by the different demographic sub-groups it seems that women doctors prescribe the product class with a slightly lower frequency than their male counterparts. White Anglo-Saxon doctors prescribe at a higher rate than their non-white counterparts, and old doctors prescribe a little more frequently than young ones. Doctors who have dispensaries attached to the practice prescribe at a slightly lower rate than do non-dispensing G.P.s. The extent of these differences is not large - the largest difference means that young doctors write one less new prescription a week compared to older ones.

However, compared to the overall rate for the product class, young doctors prescribe about one fifth less than the average. (These differences may be even less significant, given the nature of the method of categorising the age of the panel member as noted in Section 2.4).

Using the same methodology as the previous section, these differences can be explored in terms of the rarity of the type of doctor - the actual nature of the demographic

characteristic does not appear to matter. Table 3.15 represents table 3.14 in decreasing order of size.

**Table 3.14 Average Penetrations and Prescription Frequencies: Musculo-Skeletals**

	Total Number of Prescriptions	Total Number of Prescribers	Overall Prescription Frequency
Total Musculo-skeletals	49,057	243	202
Male	42,557	206	207
Female	6,500	37	176
British	37,704	182	207
Other	11,353	61	186
Old	29,532	127	232
Young	19,525	116	168
Small	13,241	77	172
Medium	21,508	102	211
Large	14,308	64	224
No Dispensary Dispensers	43,001 6,056	211 32	204 189

**Table 3.15 Average Penetrations and Prescription Frequencies: Musculo-Skeletals**

	TOTAL NUMBER OF PRESCRIPTIONS	TOTAL % OF PRESCRIBERS	OVERALL PRESCRIPTION FREQUENCY
Total	49,057	100	202
No Dispensary	43,001	87	204
Male	42,557	85	207
British	37,704	75	207
Old	29,532	52	232
Medium	21,508	42	211
Young	19,525	48	168
Large	14,308	26	224
Small	13,241	32	172
Other	11,353	25	186
Female	6,500	15	176
Dispensers	6,056	13	189

In general, there is a tendency for prescription frequencies to decline in line with the number of doctors in the

category. The main discrepancy apart from age (noted above) is that doctors with large practices seem to prescribe at a rate about 10% above average (the expected pattern noted in Section 3.2).

In order to examine whether this pattern is specific to musculo-skeletal, the same analysis was conducted with the cardiovascular data. Table 3.16 shows the variation in prescription frequency by demographic sub-group.

**Table 3.16 Average Number of Prescribers and Prescription Frequencies: Cardiovasculars**

	Total Number of Prescriptions	Total Number of Prescribers	Overall Prescription Frequency
Total Cardiovasculars	15,594	243	64
Male	13,678	206	66
Female	1,916	37	52
British	11,081	182	61
Other	4,513	61	74
Old	8,155	127	64
Young	7,439	116	64
Small	5,068	77	66
Medium	6,258	102	61
Large	4,268	64	67
No Dispensary	13,967	211	66
Dispensers	1,627	32	51

Like the musculo-skeletal product class, all doctors prescribed the product class during the year. During an average week, a doctor would write just over one new or change of prescription, a rate much lower than the musculo-skeletal product class. Cardiovasculars are therefore more like grocery products in terms of inter-purchase times, but like musculo-skeletal, the product class penetration is 100%.

The demographic sub-groups show some patterns which are similar to musculo-skeletal, and others which are slightly

different. Male doctors again appear to prescribe more frequently than females, but the size of the practice appears not to influence prescribing behaviour. Those doctors who dispense their own prescriptions do so at a lower rate, in a similar way to musculo-skeletals. In the case of ethnic origin, the demographics show the opposite pattern to musculo-skeletals with White Anglo-Saxon G.P.s prescribing at a lighter rate than their 'non-WASP' counterparts. Prescribing rates do not vary with age.

Repeating the ordering exercise shown above again reveals the extent to which the patterns are dependent on the size, not the nature of the demographic grouping (table 3.17).

**Table 3.17 Average Penetrations and Prescription Frequencies: Cardiovasculars**

	Total Number of Prescriptions	Total % of Prescribers	Overall Prescription Frequency
Total	15,594	100	64
No Dispensary	13,967	87	66
Male	13,678	85	66
British	11,081	75	61
Old	8,155	52	64
Young	7,439	48	64
Medium	6,258	42	61
Small	5,068	32	66
Other	4,513	25	74
Large	4,268	26	67
Female	1,916	15	52
Dispensers	1,627	13	51

Lidstone (1989) is another writer who proposes a segmentation procedure for pharmaceuticals and considers only type and size of GP practice as relevant, but it is unclear whether he is referring to doctor or patient demographics (or both). The analyses in this section show that it would be inadvisable for a pharmaceutical company to develop a targeting strategy based only on demographic segmentation.

### 3.7 Differences due to Demographics & Diagnosis

The simplest way to look for variation is to compare the share of prescriptions written by doctors in each demographic sub-group for each diagnosis. If there are significant differences in the shares then this could form the basis of a market partition and therefore differentiated marketing programmes could be designed to reflect this observation.

Table 3.18 shows this analysis and that in general, there is little variation in the diagnosis shares when comparing the demographic sub-groups. As far as the marketing manager is concerned, this means that a campaign directed towards a specific usage situation for one demographic category is highly unlikely to result in a dramatic response. Nevertheless the overall pattern of stability would provide a norm against which the results of a targeted campaign could be evaluated.

It seems that neither demographics nor usage situation would form a basis for real competitive advantage through segmentation or branding.

**Table 3.18 Share of Prescriptions by Diagnosis and Demographic Sub-Group of Doctor**

	Ma- le	Fem- ale	Bri- tish	Ot- her	Old	You- ng	Sma- ll	Med- ium	Big	No- Dis.	Dis- pens
M1	86	14	76	24	60	40	29	40	31	88	12
M2	85	15	70	30	61	39	34	42	24	90	10
M3	87	13	78	22	60	40	26	46	29	87	13
C1	87	13	71	29	56	44	35	40	25	90	10
C2	88	12	71	29	50	50	21	38	31	90	10
C3	90	10	72	28	43	57	27	42	31	88	12
C4	85	15	75	25	48	52	29	39	32	89	11
C5	87	13	66	34	62	38	36	44	20	89	11
Av	87	13	72	28	55	45	30	41	29	89	11

Key M1-M3 = the 3 Musculo-skeletal diagnoses  
C1-C5 = the 5 Cardiovascular Diagnoses

### 3.8 The Relationship between the Number of Prescriptions Written and the brand Portfolio

Section 3.2 described the individual heterogeneity found in prescribing, but did not explore the nature of any relationship between prescribing frequency and the number of entities utilised. This relationship is of interest in terms of making a tentative start in the understanding of consideration set sizes relative to product usage, and it was explored using four approaches ranging from contingency table analysis to model fitting.

#### 3.8a Contingency Table Analysis

Firstly, at the individual product field level and also the joint product field level, doctors were classified into categories according to their rate of prescribing and also the number of brands they used during the year.

Contingency tables were generated to see whether any relationship existed between these two variables, and an example for the two product fields combined is shown in table 3.19. In this analysis, doctors were placed into one of 6 categories depending upon their overall frequency of prescribing and one of 5 depending upon the number of entities they used.

Table 3.20 reports the chi-square statistics for the three contingency tables and indicates that the relationship between the number of brands used and the overall frequency with which doctors prescribe is non-random. Some caution is required given the strict non-independence of the samples but the pattern observed in table 3.19 indicates that the relationship is significant.

**Table 3.19 Cross-Tabulation of Prescribing Frequency and Number of Entities used, for Both Product Fields Combined**

48 Weeks	<u>Number of Brands</u>					
<u>No. of Scripts.</u>	1-19	20-29	30-39	40-49	50-60	Total
1 - 99	12 (57%)	9 (15%)	2 (3%)			23 (10%)
100 - 199	5 (24%)	26 (44%)	25 (33%)	8 (14%)		64 (26%)
200 - 299	1 (5%)	16 (27%)	33 (43%)	23 (40%)	5 (17%)	78 (32%)
300 - 399	2 (10%)	6 (10%)	11 (15%)	13 (22%)	11 (38%)	43 (18%)
400 - 499	1 (5%)	1 (2%)	3 (4%)	8 (14%)	4 (14%)	17 (7%)
500+		1 (2%)	2 (3%)	6 (10%)	9 (31%)	18 (7%)
Col. Tot.	21 (9%)	59 (24%)	76 (31%)	58 (24%)	29 (12%)	

It was not practical to extend this analysis to the diagnostic sub-categories due to the frequency of expected low cell counts at this level of aggregation.

**Table 3.20 Chi-square Statistics Showing the Relationship Between Prescriptions Written and Number of Brands Used**

DF=20	chi-square	p
Joint Field	144	0
Musculo-skeletals	102	0
Cardiovasculars	365	0

The analysis shows however that not only do 'heavy' prescribers use more entities than one would expect were

there no association, but that 'light' prescribers use fewer entities.

### 3.8b Regression Analysis

The contingency table analysis indicated a positive relationship between the number of entities used and the number of prescriptions written. In an attempt to examine the nature of this relationship simple linear regression was employed using the continuous data for the number of entities used and the number of prescriptions written.

The results of the regression analysis covering both product fields together are shown in table 3.21 and while these results are statistically significant, the relationship leaves over 60% of the variance in 'portfolio size' unexplained by weight of prescribing.

The model as it stands could be operationalised by saying that on average a doctor has an initial consideration set of about 20 chemical entities and when he or she has written 20 new prescriptions another brand will be added to the portfolio. So a doctor writing 100 prescriptions a year will use about 25 brands and one who writes 300 per year will use about 35 brands per year, and so on.

This model only fits the data from which it is derived and one would need to repeat the analysis for subsequent years to see whether or not the summary measures changed in order to evaluate it as a predictive tool.

**Table 3.21 Relationship Between Prescriptions Written and Number of Brands Used (Both Product Fields Combined)**

Parameter	Estimate	SE	T	p
Intercept	22	1	19	0
Slope	0.05	0.004	12	0

Analysis of Variance					
Source	Sum of Squares	Df	Mean Square	F	p
Model	13094	1	13094	154	0
Error	20430	241	84		

R-squared 39%					
---------------	--	--	--	--	--

The analysis was repeated for the product class and diagnosis levels to see whether or not any obvious patterns existed. Table 3.22 shows the size of each category along with the adjusted r-squared value and slope of each regression equation.

**Table 3.22 Relationship Between Prescriptions Written and Number of Brands Used**

Category	Number of Prescriptions	r-squared	slope
All	65,000	.4	.05
Musculo-skel	50,000	.3	.05
Cardiovas.	15,000	.6	.2
Other Musc.	32,000	.3	.06
Rheum. Arth.	15,000	.4	.1
Hypertension	8,000	.6	.3
Angina	3,500	.5	.4
Heart Failure	2,500	.6	.5
Osteo Arth.	2,000	.3	.3
Arrhythmia	800	.5	.8
Other Card.	700	.6	.8

Table 3.22 does not reveal any simple reproducible findings which could be generalised. For example, the two regression equations relating to the different product fields here are dissimilar but there are some

patterns which can be noted and could be compared with other product fields and even market situations.

Firstly, the relationship between usage and portfolio size seems to be stronger for the cardiovascular product field and while there is no obvious explanation for this finding, it does seem to hold at the diagnosis level as well. Secondly, there seems to be a trend which indicates that the larger the diagnosis unit, the larger will be the number of entities considered. Of course this may be a simple reflection of the market attractiveness to suppliers and therefore the pattern could be due partly to availability as opposed to customer-based variety seeking behaviour. Thirdly, the rate at which brands are added to the 'base' repertoire seems to be inversely related to the size of the product market. This seems to hold across diagnoses within a product class but not across product classes. Further work in other product markets would be required to see if these patterns generalised.

Despite the problems with the regression approach, the analysis does confirm that a relationship between portfolio size and prescription frequency does exist despite a great deal of scatter.

The poor results of the regression approach led to the third analysis of simply plotting the number of prescriptions against the number of entities used. It became clear that a simple logarithmic transformation did not adequately model the changes in the data. A strong relationship did seem likely between the number of entities 'cubed' and the number of prescriptions written. This led to the final analytic method.

### 3.8c Data Reduction

A more transparent approach to exploring the relationship relies upon the data reduction concept (Ehrenberg 1993). In this case, each diagnosis is analysed by sorting the doctors in decreasing order of prescription frequency and computing the average number of prescriptions written and the number of brands used for each group of 20 doctors. These data are shown in tables 3.23 and 3.24.

**Table 3.23 Number of Prescriptions Written and Number of Entities Used (averages of groups of 20 doctors) - Musculo-skeletals**

1 Year	m3		m1		m2	
	Av. No. of Rxs	Av. No. of Ents	Av. No. of Rxs	Av. No. of Ents	Av. No. of Rxs	Av. No. of Ents
A	349	20	191	19	36	9
B	231	18	110	16	16	8
C	190	19	89	17	12	8
D	163	17	71	14	9	6
E	140	17	60	14	7	5
F	124	15	51	12	6	4
G	111	14	44	11	5	4
H	95	15	39	11	4	3
I	76	13	34	10	3	3
J	61	13	29	9	2	2
K	44	10	21	8	1	1
L	18	7	10	5		
Av.	133	15	62	12	9	5

**Key:** m1-m3 represent the three musculo-skeletal diagnoses.  
A-L represent groups of 20 doctors in decreasing order of prescription frequency  
Rxs = prescriptions written

**Table 3.24 Number of Prescriptions Written and Number of Entities Used (averages of groups of 20 doctors) - Cardiovasculars**

1 year	c1		c2		c3		c5		c4	
	Av. No. of Rx's	Av. No. of Ent's	Av. No. of Rx's	Av. No. of Ent's	Av. No. of Rx's	Av. No. of Ent's	Av. No. of Rx's	Av. No. of Ent's	Av. No. of Rx's	Av. No. of Ent's
A	115	16	46	8	41	9	14	4	15	6
B	66	14	29	8	22	7	8	3	7	4
C	53	12	22	7	16	7	5	3	5	3
D	42	12	18	6	13	5	4	3	3	3
E	35	10	16	6	10	5	3	2	2	2
F	28	10	12	6	8	4	2	2	1	1
G	22	8	10	5	6	4	1	1	1	1
H	17	7	8	4	4	3	1	1	1	1
I	12	7	6	4	2	2	1	1		
J	9	6	4	3	1	1				
K	7	4	2	2	1	1				
L	3	2	1	1						
Av.	34	9	15	5	11	4	4	2	4	3

**Key:** c1-c5 represent the five cardiovascular diagnoses  
A-L represent groups of 20 doctors in decreasing order of prescription frequency  
Rx's = prescriptions written

It can be seen from tables 3.23 and 3.24 that there is a clear relationship between prescription rates and the number of brands used in the 'consideration set'.

This relationship is well described by the identity:

$$E=3\sqrt[3]{P}, P>5 \quad E=P, P<6$$

Where E is the number of entities used and P is the number of prescriptions written.

Applying this identity to the data in tables 3.23 and 3.24 yields tables 3.25 and 3.26 where the excellent fit of the model can be observed.

**Table 3.25 Observed and Predicted Number of Entities Used Musculo-skeletal - 1 year**

	m3		m1		m2	
	Obs	Pred	Obs	Pred	Obs	Pred
A	20	21	19	17	9	10
B	18	18	16	14	8	8
C	19	17	17	13	8	7
D	17	16	14	12	6	6
E	17	16	14	12	5	6
F	15	15	12	11	4	5
G	14	14	11	11	4	5
H	15	14	11	10	3	4
I	13	13	10	10	3	3
J	13	12	9	9	2	2
K	10	11	8	8	1	1
L	7	8	5	6		
Av.	15	15	12	11	5	5

**Key:** m1-m3 represent the three musculo-skeletal diagnoses

A-L represent groups of 20 doctors in decreasing order of prescription frequency

**Table 3.26 Observed and Predicted Number of Entities Used Cardiovasculars - 1 year**

	c1		c2		c3		c5		c4	
	Obs	Pred								
A	16	15	8	11	9	10	6	7	4	7
B	14	12	8	9	7	8	4	6	3	6
C	12	11	7	8	7	8	3	5	3	5
D	12	10	6	8	5	7	3	3	3	4
E	10	10	6	7	5	6	2	2	2	3
F	10	9	6	7	4	6	1	1	2	2
G	8	8	5	6	4	5	1	1	1	1
H	7	8	4	6	3	4	1	1	1	1
I	7	7	4	5	2	2			1	1
J	6	6	3	4	1	1				
K	4	6	2	2	1	1				
L	2	3	1	1						
Av.	9	9	5	6	4	5	3	3	2	3

**Key:** c1-c5 represent the five cardiovascular diagnoses

A-L represent groups of 20 doctors in decreasing order of prescription frequency

The degree of fit between the observed and predicted number of brands used in tables 3.24 and 3.25 is close with an r squared value of 0.95. This simple model works well across the different diagnoses and also the two product classes, and the same constant, 3, works despite differences in product type and overall frequency of prescription.

Empirical testing on other data sets would be needed to see whether the form or parameters of the relationship hold in different product market situations - given data availability on purchase frequencies above 5, or whether a more general form is applicable ie:

$$E = k * \sqrt{P}$$

Where E is the number of entities used and P is the number of prescriptions written.

### 3.9 Similarities and Differences Between Prior Studies

This section highlights some of the key differences and similarities between these data and those which form the basis of prior research in the buyer behaviour area.

#### 3.9a Heterogeneity

The patterns of individual heterogeneity in **Sections 3.2 - 3.4** mirror those found in many previous empirical studies of buyer behaviour in fmcg markets which show no trend in sales, except that here the frequency distribution has a mode greater than zero. This is similar to visiting retail outlets and buying petrol (for car owners).

In the case of Arrythmia in **Section 3.4**, the mode is 1, but otherwise the shape of the distribution is similar to many buying situations studied by other researchers, (See for example Herniter, 1971).

It is worth stressing again that the degree of heterogeneity in these data (a factor of 100 difference between the heaviest and lightest prescribers) is far greater than previous studies.

### 3.9b The Buyer

The buyers in this study are professionals who have received broadly similar training in terms of diagnosis and treatment. They are valued by society and regarded as highly rational individuals. This would lead to the conclusion that their behaviour should be relatively homogeneous, especially when compared to purchases of largely non-essential household items.

While it is reasonable to explain the heterogeneity of household purchase patterns in terms of subjective propensity, it seems extraordinary that prescribing is similarly explained. It is even more enlightening that doctors behave differently in different diagnosis situations and product classes.

### 3.9c Non-Buyers versus Infrequent Buyers

It is perhaps important to distinguish between two different effects which derive from different population definitions. There will be some product classes that are (virtually) never purchased by some households (eg pork by orthodox Hindu or Jewish households) and others where the overall purchase frequency is so low, that some households have not purchased during the analysis period (eg icing sugar). In his comment on Morrison and Schmittlein (1988), Montgomery (1988) questions whether the proportion of product class non-buyers is likely to bias buyer behaviour estimates derived from the Negative Binomial Distribution, and hence hinder cross-product class comparison. As examples, he cites dog food which was purchased by just 33% of the Chicago Tribune consumer panel and soaps and detergents which were bought by virtually everyone.

It is likely that a significant proportion of the population will never own a dog and therefore never buy dog food. In these cases, non-buyers might be an issue (see also Massy, Montgomery and Morrison, 1970, p. 337). In practice, the fit of the NBD-Dirichlet is good as long as the proportion of non-buyers is large enough (Ehrenberg, 1988, p. 76).

However, it may well be that virtually all the 59% of the Chicago Tribune panel who had not purchased bourbon (another product class included in the panel), would in fact do so at some time in the future, and therefore the distinction between buyer and non-buyer will tend to disappear if the length of the analysis period is sufficient.

The problem of non-buyers has not been eliminated in prior studies, as increasing the length of the analysis period means that in the long run most markets are non-stationary and this reduces the predictive power of NBD type models.

In this data on doctor prescribing, the short times between prescriptions means that for even the most infrequent diagnosis, the majority of doctors prescribe the class at least once and therefore the proportion of non-prescribers is in general very small. This means that this research is able to look at behaviour in market situations with low/zero proportions of non-users and high frequency of use within a stationary constraint.

In Chapters 4 and 6 the distributions of prescription frequency are tabulated and compared to those predicted by the NBD-Dirichlet. Using these and other measures, it will then become clear how similar prescribing patterns are to purchasing household products.

### 3.10 Summary

Throughout Chapter 3 similar patterns are found to those in fmcg studies despite a radically different marketing situation.

- The market shows little variation in terms of the proportion of prescribers and their prescription frequency in time periods of the same length. This stability applies at the levels of diagnosis and product class.
  
- There is very high heterogeneity at the levels of combined product fields. The lightest prescriber writes 9 prescriptions in a year and the heaviest writes over 1000. The smallest number of entities used is 8 and the largest is 63 in the year.
  
- This heterogeneity is also found at the product class and diagnosis level. For musculo-skeletal, the number of prescriptions written ranges from 3 to 800 and the number of entities used ranges from 2 to 35 during the year. The corresponding figures for cardiovasculars are a prescription range of 2 to 324 and an entity range of 1 to 33.
  
- The size of the practice only accounts for about 10% of the variance in prescription frequency, and subjective propensity is likely to account for the degree of heterogeneity observed.
  
- The size of the practice does not influence the range of entities used by the doctors.
  
- A heavy prescriber in one diagnostic category will not necessarily be a heavy prescriber in other diagnostic categories or the other product field, and yet the summary measures of prescribing are largely predictable from the overall category size. This means that the subjective

propensities of individual doctors change with the diagnosis and product class.

- The rates and range of prescribing are comparable with some product classes in a retail environment, and the current research might provide some insights into this aspect of marketing.

- The diagnoses and product fields have a 'Double Jeopardy' type pattern with common diagnoses having more prescribing doctors who prescribe more frequently than rare diagnoses. The pattern is visible despite the fact that the diagnoses are very different.

- Doctors prescribe brands more frequently than their generic equivalents, but once the size of the category is accounted for, generics attract the same prescribing frequencies as brands. The implication is that individual brands will not attract any greater levels of loyalty than their generic equivalents. This will be examined in detail in **Chapter 8**.

- Demographic variables have little effect on prescribing behaviour. Where a (small) difference is found, it is not consistent across product classes.

- A combination of demographic variables and usage situation (reflected in diagnosis) show no significant differences in prescribing behaviour. This means that successful marketing plans are unlikely to result from targeting using these bases.

- There is a simple relationship between the number of brands in the doctor's portfolio and the number of prescriptions written. It applies across the different diagnoses and the two product fields.

When the behaviour of doctors is examined at the aggregate level, the patterns from week to week, month to month and quarter to quarter are largely stable and similar. This aggregate homogeneity overlays an extremely high degree of individual heterogeneity when comparing individual doctor behaviours at different levels of product market analysis. This extreme heterogeneity where individual behaviour varies by a factor as large as 100 is in itself an important empirical finding which cannot be explained by the number of patients on the doctors' lists. The patterns are, however, familiar from studies of fast moving consumer goods markets. Modelling the effect is considered in **Chapter 6**.

The analyses completed in the present chapter show that branded pharmaceuticals are prescribed in the same way as their generic counterparts, and once the size of the diagnostic category is taken into account brands are not on the whole favoured when compared to generics.

This chapter also reveals that the differences in prescribing behaviour when comparing doctors by demographic variables are very small and largely predictable from the numbers in the population rather than any intrinsic behavioural heterogeneity across groups of doctors. It therefore challenges prior studies which assume that a priori segmentation based on attitudinal data will result in more efficient marketing programmes.

The chapter concludes that there is a simple relationship between a doctor's frequency of prescription and the number of entities included in the repertoire.

**CHAPTER 4: DESCRIPTIVE DATA PATTERNS****Overview****4.1 Introduction****4.2 Double Jeopardy****4.3 Growth in Penetration and Frequency****4.4 Distribution of Prescriptions****4.5 Prescribing the Product Class and Natural Monopoly****4.6 Share of Requirements****4.7 Duplication of Prescriptions****4.8 Variation in Penetration and Prescription Frequency****4.9 Duplications between Chemical Equivalents****4.10 Conclusions**

### Overview

1. Entities which command a large share of prescriptions benefit from the familiar Double Jeopardy pattern - they have a larger number of doctors who prescribe, and they are prescribed more frequently than small entities.
2. When the product class purchase frequency is low (or the length of the analysis period is short) then entities differ more in their penetrations than in their prescription frequencies.
3. When a product class is prescribed frequently, the majority of doctors prescribe the leading entities in the product class. This means that entities begin to differ more in terms of prescription frequency than penetration.
4. The distribution of prescription frequencies for individual entities is reverse 'J' shaped and similar for the different product fields and diagnoses.
5. One entity (Capoten) stands out as being different to the rest.
6. Individual entities in pharmaceutical prescribing also follow the well established Natural Monopoly pattern found in fast moving consumer goods markets.
7. Entities with large market shares account for a higher proportion of prescribing requirements than entities with small shares. There are, in general, no entities which account for specific market niches, although there is an exception to this generality.
8. There is no evidence of strong market partitioning as measured by the propensity of doctors to prescribe pairs of entities specifically or exclusively. This provides further refutation (see Chapter 3, Sections 6 & 7) for a segmented marketing approach.

9. There is, however, evidence of partitioning between some specific chemical entities. Doctors who prescribe a branded drug of one 'strength' are more likely (than the average doctor) to prescribe the same drug in a different strength.

In contrast, doctors who prescribe the branded form of a drug are less likely to prescribe the generic version of the same drug. This varies by individual entity, so that in some cases there is little or no partitioning between the brand and its generic equivalent.

#### 4.1 Introduction

This chapter describes several patterns within the data on G.P. prescribing which are similar when compared with established empirical knowledge. It also describes some specific exceptions to those previously found patterns.

In **Section 4.2** the relationship between the proportion of prescribers and their prescription frequency is detailed showing the familiar Double Jeopardy pattern. The way in which the sales of an entity grow through relatively short time periods is examined in **Section 4.3** (sales growth in longer time periods is examined in **Section 4.8**) and then in **Section 4.4** the distribution of purchase frequencies among prescribers is analysed. **Section 4.5** looks at the product class prescribing rates and **Section 4.6** examines the share of total requirements accounted for by each entity. **Section 4.7** analyses the general patterns of prescription duplication between different drugs.

The last part of this chapter looks at some exceptions to the established patterns. **Section 4.8** examines variations in penetration rates and prescription frequencies for entities during a year (rather than the shorter time periods examined in **Section 4.3**). The chapter concludes in **Section 4.9** with

some instances of lower than expected duplication rates between chemically identical drugs.

Following the presentation of these analyses, the data patterns are evaluated and the subsequent implications are considered in terms of modelling methodologies.

#### 4.2 Double Jeopardy

Tables 4.1 and 4.2 show the proportion of prescribers and how often they prescribed some large and small entities in the first quarter of 1986. The entities chosen for illustration here were selected from tables generated from the original panel data using programmes specially written for the software package DBASE 3+. In the case of musculo-skeletal, there were 57 different chemical names in the analysis (along with all others) and for cardiovasculars, 41 different names were used.

Tables which illustrate all the entities are undesirable because they would be very difficult to interpret due to the volume of information. However, the patterns reported here generalise across all the entities in both product fields. For the purpose of illustrating these patterns, five large and five small entities were selected from each product class. In the case of musculo-skeletal, the large entities selected accounted for just over a third of all prescriptions written in the quarter and the corresponding figure for cardiovasculars was just over 20%.

In general, there is a tendency for entities with large shares to benefit in two ways: they have more prescribing doctors and those doctors prescribe more frequently than for entities with small shares.

For example, the leading musculo-skeletal, Brufen, was prescribed by almost two thirds of doctors and they prescribed it just over nine times on average during the quarter. On the other hand, Prednisolone was used by under

10% of the G.Ps and they prescribed it just 1.5 times during the quarter.

**Table 4.1 Quarterly Penetration and Prescription Frequencies for ten Musculo-skeletal drugs**

12 weeks	Market Share (%)	b	w
Brufen	11	64	9.1
Coproxamol	8	60	6.9
Naprosyn	8	58	6.9
Feldene	5	55	5.2
Lederfen	3	38	4.6
Indocid R	1.7	26	3.3
Benoral	1.4	23	3.2
Dolobid	0.9	19	2.6
Meptid	0.4	10	2.4
Prednisolone	0.2	9	1.5
Average		36	4.6

**Table 4.2 Quarterly Penetration and Prescription Frequencies for ten Cardiovascular drugs**

12 weeks	Market Share (%)	b	w
GTNT	5.0	43	2.1
Capoten	4.9	17	5.0
Tenormin	4.1	37	2.0
Adalat	3.7	33	2.0
Atenolol	3.5	28	2.2
Dyazide	1.7	19	1.6
Tenoretic	1.5	18	1.5
Verapamil	1.1	13	1.6
Tenoret	1.0	11	1.6
Rythmodan	0.3	4	1.2
Average (excluding Capoten)		20	1.7

Turning to the cardiovascular product field a similar pattern is found with a notable exception. The largest entity, GTNT, is prescribed by just under half of all

doctors with an average frequency of just above 2. As the shares drop, penetration and frequency tend to drop so that Rythmodan, a very small brand, is prescribed by just 4% of G.Ps with a frequency of just over one in the quarter. One might say that Atenolol presents a slight anomaly with a slightly high frequency of prescription given its penetration, but the entity which stands out as failing to fit the pattern is Capoten which is prescribed at over twice the average rate by a somewhat smaller number of doctors. So in the case of prescribing drugs, the familiar Double Jeopardy pattern is evident, along with one anomalous brand requiring further explanation (see Chapter 9).

In Chapter 7, Double Jeopardy will be analysed at the diagnosis level to provide eight further opportunities to test the pattern.

#### **4.3 Growth in Penetration and Frequency**

Taking the data in tables 4.1 and 4.2, the length of the analysis period can be extended to a year to explore how the components of market share change. Tables 4.3 and 4.4 show the relevant data for the same entities.

Looking first at the cardiovasculars, it can be seen that as the analysis period increases by a factor of four, on average both penetration and prescription frequencies roughly double. However, for the smaller entities the rate of increase in penetration outstrips that of prescription frequency.

Turning to the musculo-skeletal, a slightly different pattern is evident, with prescription frequency growing on average, at a faster rate than penetration.

In a stationary market where total prescriptions grow proportionately with time, the penetration and purchase frequency will each grow less than proportionately (unless one or the other is also stationary).

**Table 4.3 Quarterly and Annual Penetrations and Prescription Frequencies**

Cardio-vasculars	quarter		year	
	b	w	b	w
GTNT	43	2.1	71	3.9
Capoten	17	5.0	32	9.6
Tenormin	37	2.0	57	4.4
Adalat	33	2.0	60	4.1
Atenolol	28	2.2	48	5.1
Dyazide	19	1.6	38	3.6
Tenoretic	18	1.5	45	2.7
Verapamil	13	1.6	36	2.6
Tenoret	11	1.6	29	3.0
Rythmodan	4	1.2	10	1.8
Average (excluding Capoten)	23	1.8	44	3.5

**Table 4.4 Quarterly and Annual Penetrations and Prescription Frequencies**

Musculo-skeletals	quarter		year	
	b	w	b	w
Brufen	64	9.1	85	26.2
Coproxamol	60	6.9	79	21.6
Naprosyn	58	6.9	79	16.8
Feldene	55	5.2	77	13.3
Lederfen	38	4.6	63	10.0
Indocid R	26	3.3	49	5.6
Benoral	23	3.2	47	6.5
Dolobid	19	2.6	35	6.6
Meptid	10	2.4	20	4.7
Prednisolone	9	1.5	21	3.0
Average	36	4.6	56	11.4

A large entity like Brufen which already has 64% of doctors prescribing in a quarter cannot achieve a penetration growth of more than half no matter what length of period is

analysed. By definition then, growth in average prescription frequency must be faster than penetration for such entities.

This pattern of penetration and prescription frequency growth for cardiovascular prescriptions is similar to that found in fast moving grocery product markets. The pattern for musculo-skeletal differs in that the increase in sales derives more from growth in prescription frequency than penetration (see Section 4.8 below).

#### 4.4 Distribution of Prescriptions

The study of the two product classes is analogous to examining buyer behaviour in two different product fields in the grocery market which differ in their purchase frequency. Generalisations about prescribing behaviour could be made if similar patterns continue to emerge in both product fields and further that these patterns are similar to those which have already been observed in other marketing situations.

Tables 4.1 and 4.2 showed the penetration and average prescription frequencies of a range of entities from both product fields. Of course, no doctor actually prescribed at the average rate and each entity has a distribution of prescription frequencies about the average rate. These distributions are shown in tables 4.5 and 4.6. Here the entities are organised in decreasing market share order and there are consistent trends found in both sets of data.

Firstly, all entities have at least 50% of doctors prescribing four times or less in the quarter. Secondly, as market share decreases, the proportion of 'light' prescribers increases. GTNT, the largest cardiovascular entity, has half of its prescribers prescribing just once in the quarter, whereas just under 80% of the Rythmodan prescribers use it once in the quarter. Brufen, the musculo-skeletal market leader, has 15% of its prescribers using it once compared to the small entity Prednisolone where almost three quarters of doctors prescribe it just once.

The third common trend is a decreasing frequency of prescribing as the prescription rate increases and the shape of each distribution is of the reverse J form. This is somewhat less clear in the case of the musculo-skeletal product class due to the relatively large number of doctors who prescribe with a frequency greater than 9 times in the quarter.

The one entity which stands out as being different from the others is the cardiovascular entity Capoten which seems to have fewer light prescribers and a surfeit of heavy prescribers when compared to other entities in the product field. However, this very simple analysis facilitates the observation that Capoten appears to be different and therefore directs the further analysis which is discussed in detail in Chapter 9.

**Table 4.5 Distribution of Musculo-skeletal Prescriptions**

12 weeks	Percent of Doctors writing 1,2,3,.... Prescriptions								
	1	2	3	4	5	6	7	8	9+
Any	0	0	0	0.4	0.4	0.4	1.2	0	97.2
Brufen	15	17	7.7	9.7	7.1	2.6	1.9	6.5	32.3
Coproxamol	25	12	8.9	8.2	4.1	4.8	5.5	6.2	26.0
Naprosyn	24	18	5.7	9.3	7.1	5.7	2.9	5.7	22.1
Feldene	37	17	12.1	4.5	4.5	5.3	0.8	3.0	16.0
Lederfen	36	15	8.6	14.0	4.3	5.4	1.1	1.1	14.9
Indocid R	44	22	7.8	14.1	1.6	1.6	0	0	9.2
Benoral	49	11	10.9	5.5	7.3	3.6	1.8	0	10.9
Dolobid	55	17	6.4	6.4	2.1	0	2.1	2.1	8.6
Meptid	52	30	4.3	4.3	0	0	4.3	0	4.5
Prednisolone	73	18	0	9.1	0	0	0	0	0
Average	41	18	7.2	8.5	3.8	2.9	2.0	2.5	14.5

**Table 4.6 Distribution of Cardiovascular Prescriptions**

12 weeks	Percent of Doctors writing 1,2,3,.... Prescriptions								
	1	2	3	4	5	6	7	8	9
Any	6	3	4.7	3.4	3.4	3.8	3.0	1.7	71.2
GTNT	50	24	13.9	6.9	0	3.0	1.0	1.0	1.0
Capoten	34	7	9.8	7.3	4.9	9.8	0	2.4	24.4
Tenormin	57	22	9.1	4.5	2.3	3.4	1.1	0	1.1
Adalat	54	23	14.1	1.3	2.6	2.6	1.3	0	1.3
Atenolol	48	19	16.4	7.5	7.5	0	0	0	1.5
Dyazide	61	27	6.8	2.3	0	2.3	0	0	0
Tenoretic	74	12	4.8	9.5	0	0	0	0	0
Verapamil	60	27	10.0	3.3	0	0	0	0	0
Tenoret	60	28	8.0	0	0	4.0	0	0	0
Rythmodan	70	22	0	0	0	0	0	0	0
average	58	21	9.3	4.3	1.7	2.5	0.3	0.3	2.9

Similar trends have been observed before in the study of fmcg markets where patterns have been successfully modelled using the Negative Binomial Distribution, and results using this model for these data sets can be found in **Chapter 6**.

Overall, the distributions of prescription frequencies are similar to those that have been observed in numerous other buyer behaviour studies.

#### **4.5 Prescribing the Product Class and Natural Monopoly**

Tables 4.7 and 4.8 show the rate at which the prescribers of each entity prescribe the product class as a whole. Thus, the 155 prescribers of Brufen wrote just over 8500 prescriptions for musculo-skeletals in the quarter giving the average product class prescription frequency (wp) of 56.

The tables also show that within each product field the product class prescribing rate varies little from entity to entity, although there is some evidence of a trend for slightly higher product class prescription frequencies to be associated with the smaller entities, and the opposite trend for large entities. Again Capoten shows a clear exception to the general pattern.

This trend is illustrated more clearly in table 4.9 where the average product class prescription frequencies of large medium and small entities is shown. It is small but

**Table 4.7 The Rate of Product Class Prescribing Musculo-skeletals**

12 weeks Musculo- skeletal	Market Share (%)	wp
Brufen	11	56
Coproxamol	8	61
Naprosyn	8	60
Feldene	5	58
Lederfen	3	60
Indocid R	1.7	62
Benoral	1.4	70
Dolobid	0.9	61
Meptid	0.4	61
Prednisolone	0.2	65
Average		61

**Table 4.8 The Rate of Product Class Prescribing Cardiovasculars**

12 weeks Cardio- vasculars	Market Share (%)	wp
GTNT	5.0	24
Capoten	4.9	28
Tenormin	4.1	24
Adalat	3.7	23
Atenolol	3.5	23
Dyazide	1.7	22
Tenoretic	1.5	25
Verapamil	1.1	29
Tenoret	1.0	26
Rythmodan	0.3	25
Average (excluding Capoten)		25

**Table 4.9            Aggregated Product Class  
Prescription Frequencies**

Musculo-skeletals	wp(average)
Large (15 entities)	62
Medium (15 entities)	63
Small (15 entities)	64
Average	63
<b>Cardiovasculars</b>	
Large (15 entities)	25
Medium (15 entities)	26
Small (12 entities)	27
Average	26

consistent and has been noted many times before in studies of fmcg markets (see Ehrenberg 1988).

Here then is another empirical pattern which is common to drug prescribing and the purchase of groceries. It is modelled in Chapter 6.

#### **4.6 Share of Requirements**

By comparing the average entity prescription frequencies with those of the product class, a measure of loyalty that each entity attracts can be determined. This is shown in table 4.10 where the entities are arranged in decreasing order of prescription share.

This table shows that the large entities account for a higher proportion of their prescribers' needs than do small entities. There is no evidence of any small entities which occupy specific niches where they account for a dominant proportion of their users requirements.

Again Capoten stands out as an entity which shows a somewhat different pattern accounting for about a fifth of its prescribers needs. This entity attracts the highest degree of loyalty of any of the entities but even so, the doctors

who use it devote over 80% of their requirements to other entities.

**Table 4.10 Share of Product Class Prescriptions Accounted for by Selected Entities**

Entity	Share of Requirements
<b>Musculo-skeletals</b>	<b>%</b>
Brufen	16
Coproxamol	11
Naprosyn	12
Feldene	9
Lederfen	8
Indocid R	5
Benoral	5
Dolobid	4
Meptid	4
Prednisolone	2
<b>Cardio-vasculars</b>	
GTNT	9
(Capoten	18)
Tenormin	8
Adalat	8
Atenolol	10
Dyazide	7
Tenoretic	6
Verapamil	5
Tenoret	6
Rythmodan	5

This is, therefore, a market characterised by low loyalty levels, which is yet another pattern consistent with many fmcg markets which have been studied previously.

#### **4.7 Duplication of Prescriptions**

The pattern of competition between specific entities can be examined by looking at the proportion of doctors who prescribe a pair of entities, say, Brufen and Coproxamol and comparing this figure with the average proportion of prescribers of any entity also prescribing Coproxamol.

In fast moving consumer goods markets which have been studied, the patterns of buying duplications are highly predictable and dependent on entity penetrations alone.

The patterns for pharmaceutical prescribing are shown in tables 4.11 and 4.12. Looking at the first row of table 4.11 we see that of the doctors who prescribed Brufen in the quarter, 68% also prescribed Coproxamol and 65% also prescribed Naprosyn and so on. As the entities across the first row decline in penetration, so also does the percentage of Brufen prescribers, so that only about 10% of Brufen prescribers also prescribe Prednisolone.

The tables are most easily interpreted by reading down each column, thus Coproxamol is prescribed by 68% of the doctors who prescribe Brufen, 64% of the doctors who prescribe Naprosyn and so on. All the figures in this first column are quite close to the average of 67% at the foot of the column. On the other hand, Prednisolone is prescribed by about 10% of the prescribers of each of the other entities.

There are a number of examples where the entity duplications differ by more than 10% from these averages (as indicated by the figures in bold in the table). Only 56% of Meptid prescribers also prescribed Brufen in the quarter versus the 68% expected. The actual number of doctors who prescribed Meptid in the quarter was 23 and so the shortfall is only two or three doctors - not a very large effect. A similar result is seen for duplications between Meptid and Feldene where the shortfall is about five doctors. The other case of a very low duplication is between Prednisolone and Dolobid. Here the shortfall is again small in absolute terms (two doctors).

There are two cases where duplications are higher than the averages, but not dramatically so. The high duplication between Indocid R and Naprosyn represents a surfeit of 5

doctors and that between Indocid R and Dolobid a surfeit of 6 doctors.

Overall then, the percentage of duplicated buyers closely matches their entity penetrations. This is shown at the foot of tables 4.11 and 4.12 where the average of each entity's duplications is shown along with their penetrations. The averages also allow differences (such as the duplication between prescribers of Meptid and Feldene) to be highlighted.

The coefficients at the foot of each table represent the mean of each entity's average duplication divided by its penetration, and for both product fields the coefficient is close to one which means that the prescribing of one ethical pharmaceuticals entity is independent of the prescribing of

**Table 4.11 Duplication of Musculo-skeletal Prescriptions**

12 weeks										
Buyers of:	% Who also buy:									
	Bru	Cop	Nap	Fel	Led	Ind	Ben	Dol	Mep	Pre
Brufen		68	65	58	37	28	25	19	8	11
Coproxamol	73		62	57	43	32	26	23	10	10
Naprosyn	71	64		56	43	33	26	20	9	9
Feldene	68	63	60		48	28	24	24	7	10
Lederfen	61	68	64	68		32	28	19	12	11
Indocid R	69	73	72	58	47		27	30	12	8
Benoral	71	69	67	56	47	31		14	13	9
Dolobid	64	70	60	66	38	40	17		11	4
Meptid	56	65	52	39	48	35	30	22		0
Prednisol.	77	68	54	59	45	23	23	9	0	
Ave. Dup.	67	67	61	57	43	31	25	20	9	8
Pred.Dup.	68	64	61	58	41	28	24	21	10	10
Penetr.	64	60	58	54	38	26	23	19	10	9
Coef.	1.1									

another and that there are unlikely to be unique groups of doctors who have needs satisfied by specific drugs.

Yet again, this is a familiar pattern to buyer behaviour analysts.

The duplications which show large differences from the average are small in terms of actual numbers of doctors, and one simple check is to examine the duplications in a year to see whether the deviations apparent in table 4.11 are general or not. This is shown in table 4.11a.

**Table 4.11a Duplication of Selected Musculo-skeletal Prescriptions**

1 Year Buyers of:	% Who also buy:			
	Brufen	Naprosyn	Feldene	Dolobid
Indocid R		84		45
Meptid	92		78	
Prednisolone				43
Average	87	81	78	38

From this table it can be seen that in the longer time period the pattern is as one would expect, and therefore there is no special pairing of entities in this product market.

The duplication pattern for the selection of cardiovascular entities shows more variation than that for musculo-skeletals. In general, as in the case of musculo-skeletals, the duplications are much more in line with the averages when the analysis is extended from a quarter to a year. The instances where a duplication between two entities in table 4.12 remains very different from the average are summarised in table 4.12a.

The low annual duplications between Tenormin and Atenolol are considered in Section 4.9 below along with the high duplications between Tenoret and Tenoretic. This leaves the lower than expected number of Tenoret prescribers who also prescribed Adalat, as well as the duplication of Rythmodan with Tenoretic and Verapamil.

**Table 4.12 Duplication of Cardiovascular Prescriptions**

12 weeks										
	Buyers of:		% Who also buy:							
	GTN	Cap	Ter	Ada	Ate	Dya	Tec	Ver	Tet	Ryt
GTNT		16	41	35	33	22	26	21	13	4
Capoten	39		46	51	29	10	19	10	17	7
Tenormin	47	22		51	24	24	22	16	17	6
Adalat	45	27	58		28	15	19	17	9	5
Atenolol	49	18	31	33		22	24	16	9	4
Dyazide	50	9	48	27	34		25	20	11	4
Tenoretic	62	19	45	36	38	26		24	21	2
Verapamil	70	13	47	43	37	30	33		10	13
Tenoret	52	28	60	28	24	20	36	12		4
Rythmodan	44	33	56	44	33	22	11	44	11	
Ave. Dup.	50	20	47	38	31	21	23	19	13	5
Pred.Dup.	49	20	43	38	33	21	20	15	12	4
Penetr.	42	17	36	32	28	18	17	12	10	4
Coef.	1.2									

**Table 4.12a Duplication of Selected Cardiovascular Prescriptions**

1 Year						
	Buyers of:		% Who also buy:			
	Tenor	Adal	Ateno	Tenic	Vera	Tenet
Tenormin			43			
Atenolol	50					
Tenoretic						50
Tenoret		57		79		
Rythmodan				40	56	
Average	67	70	53	53	41	36

The first of these discrepancies is the largest, representing a shortfall of 10 duplicate prescribers between Tenoret and Adalat. There are three fewer doctors than expected who prescribe both Rythmodan and Tenoretic and four more than expected who prescribe both Rythmodan and Verapamil. Replication studies in subsequent years would be needed to determine whether or not these were consistent.

This form of analysis provides a simple empirical norm for predicting duplications between pairs of pharmaceuticals. The only requirement to predict the number of doctors who will prescribe a pair of entities is the penetration of both entities. If significant differences (such as those described here) are found when examining the actual data, then this provides a basis for further investigation. Some further examples are discussed in **Section 4.8** below.

It should be noted that the average duplications which appear at the foot of tables 4.11 and 4.12 differ slightly from those used in tables 4.13-4.15 in **Section 4.9** below. In tables 4.11 and 4.12, the average duplications are calculated from the 9 column entries (which have been rounded for clarity). In tables 4.13-4.15, the average duplications are calculated from data on 59 musculo-skeletal and 43 cardiovasculars.

#### **4.8 Variation in Penetration and Prescription Frequency**

Tables 4.3 and 4.4 showed the quarterly and annual penetrations and prescription frequencies of some drugs used in the two product fields.

Looking at the cardiovascular data in table 4.3 it can be seen that for both the quarter and the year, there is (in general) far more variation in penetration than prescription frequency. In the quarter, GTNT, the largest entity, is prescribed by ten times as many doctors as Rythmodan (the smallest brand), but GTNT is prescribed only twice as frequently as the small brand. In a year, the difference in penetration is seven-fold with again the largest entity having twice the average prescription frequency of the smallest entity.

In fact for both time periods, there is little variation in the prescription frequencies of any of the cardiovasculars (with the consistent exception of Capoten).

This pattern of penetration variability and frequency stability is again one which is well established in fmcg markets.

Turning to the musculo-skeletal data in table 4.4, we can see a somewhat different pattern which is shown most clearly in the annual data. In a year, four times as many doctors prescribed the leading brand Brufen than Prednisolone (a small entity), and they did so with an average frequency nine times that of the small entity. This is the reverse of the pattern seen in the cardiovascular field, and one which extends to all the entities in the product field. For the musculo-skeletonals, there is more variation in average prescription frequency than penetration. This is especially striking in the case of the four largest entities where the penetrations are all about 80% but the prescription frequencies vary by a factor of 2. Here then is a new pattern which is understandable in terms of penetration growth as discussed in Section 4.3. All the four largest musculo-skeletonals had penetrations above 50% in a quarter and so could not double in a year, and for sales to grow proportionately with time the prescription frequency would have to grow at a faster rate.

This feature is considered further in Chapter 6, when these observed data are compared with those from Dirichlet predictions.

#### **4.9 Duplications between Chemical Equivalents**

In studies of fmcg markets it has been established that closely substitutable entities tend to have high duplication of purchase. For example, households who buy one brand of bran cereal are more likely to buy another manufacturer's bran cereal than other available brands. Buyers of a flavour variant of a toothpaste brand are more likely to buy another flavour variant of the same brand than another brand (Ehrenberg, 1978). Similarly, owners of luxury cars are more likely to purchase another luxury brand than a mid-priced

one when they buy a new car (Ehrenberg and Pouilleau, 1993). Some instances of high and low duplications of prescription were noted in Section 4.7 and these and some further examples are now considered.

In the case of pharmaceutical prescribing there exist three forms of product similarity, two of which have parallels but not direct counterparts in fmcg markets. The third form has no direct counterpart in fmcg markets.

Drug companies do make available different forms of the same chemical, for example Ponstan Forte is the same chemical as Ponstan but in twice the dose (this could be considered as similar to normal and concentrated detergent, except that the differences in terms of using the wrong amount are more significant in the case of drugs). In addition, some brands have some common components but are different overall, for example Tenormin contains only atenolol where as Tenoret contains atenolol and chlorthalidone. The former is used for a single heart condition whereas the latter contains a diuretic for when water retention is also considered to be a problem. Here perhaps one could draw the parallel with different instant teas, one of which also contains powdered milk.

The third form of product similarity is that the doctor can prescribe the same item in two different ways. S/he could either specify the brand name on the prescription or alternatively the generic name. As long as the brand is protected by patent, the patient will actually receive the branded version.

With all three of these situations one could predict outcomes with regard to duplication of prescription.

#### 4.9a Different strengths of the same chemical.

If a doctor uses one strength, then s/he is more likely to use another strength of the same brand than another

brand. One would therefore expect to see higher duplications.

#### 4.9b The added ingredient.

If a doctor uses one ingredient already, s/he is more likely to use the formulation which combines an extra chemical (where needed) than either the same combination separately or a different combination. This would provide a marketing justification for launching such a product based on prescribing behaviour.

#### 4.9c The brand versus the generic

If a doctor is susceptible to branding they will write the brand name not the generic and there will be a low duplication. If a doctor favours generics, there will also be a low duplication and if they are indifferent the duplications will be in line with penetrations.

Tables 4.13, 4.14 and 4.15 explore these three situations.

Table 4.13 shows that there is some tendency for higher than average duplications to occur between the same drug presented in different strengths. For example, one would expect about 30% of the prescribers of any entity to also prescribe Ponstan but about twice this number of Ponstan Forte prescribers use Ponstan as well.

The pattern is quite consistent, but not exclusive. This means that while prescribers of Ponstan Forte are twice as likely as an average doctor to also prescribe Ponstan in a quarter they do not do so to the exclusion of other entities. These doctors will also prescribe other entities in proportion to their penetration levels. This analysis also explains the high duplications between Tenoret and Tenoretic noted in Section 4.6.

**Table 4.13          Duplication for Different Strengths  
12 weeks              of the Same Chemical**

Prescribers of:	Who also prescribe:	
Ponstan	Pon	Pof
Ponstan F	60	50
Average	33	28

Prescribers of:	Who also prescribe:	
Tenoret	Tet	Tec
Tenoretic	21	36
Average	12	22

Prescribers of:	Who also prescribe:	
Indocid	Ind	Inr
Indocid R	58	36
Average	39	29

Prescribers of:	Who also prescribe:	
Voltarol	Vol	Vor
Voltarol R	49	49
Average	34	34

Prescribers of:	Who also prescribe:	
Tenormin	Ten	Tes
Tenormin LS	63	22
Average	49	19

**Note:** the average duplication is calculated from 59 entities for musculo-skeletal and 43 for cardiovasculars.

In the first instance, therefore, the outcome is as predicted, but the size of the effect differs between entities in the same product class and also across the two product classes. In managerial terms this would indicate that there are no obvious shortcomings in following such a strategy.

In order to evaluate efficacy, one would have to compare the outcome with that of marketing a single brand name in a variety of available strengths, and also take into account different dosages as specified by the doctor. Such data is not available from within the current research database, and therefore the analysis is limited to the conclusion that there are no disadvantages, in prescribing behaviour terms, to the strategy (assuming that no extra marketing costs are incurred).

**Table 4.14**            **Duplication for Added**  
**12 weeks**            **Ingredients**

Prescribers of:	Who also prescribe:
Tenormin	Ten Tec 22
Tenoretic	45
Average	49    22

Prescribers of:	Who also prescribe:
Frumil	Fru Frs 24
Frusemide	26
Average	28    27

Prescribers of:	Who also prescribe:
Kalten	Kal Mod 32
Moduretic	13
Average	17    40

Note: the average duplication is calculated from 43 cardiovascular entities.

The case of added ingredients is exemplified in table 4.14 where each of the entity pairs contain at least one common chemical, but the second entity contains one more active ingredient than the first.

In this case there seems to be no special tendency for doctors who prescribe one chemical entity to use the same one in conjunction with another. The duplications are close to those predicted from the penetration levels.

One tentative conclusion is that while such product development is justifiable because it satisfies a real market need in terms of prescription or consumption convenience, it does not appeal to a specific segment of doctors who are already 'prone' to prescribing one or other of the components.

The third situation where the duplications for brands and generics is analysed is shown below in tables 4.15a,b and c. In all cases, the brand is shown first and the generic is the second of the pair.

In table 4.15a there appears to be some partitioning in that a doctor who prescribes one of the pair is less likely to prescribe the other than an 'average' doctor.

The trend is much less pronounced for the entities in table 4.15b and here the duplications are only marginally lower than average for all doctors.

In table 4.15c, the trend is in fact reversed, although because the total number of prescribers of Ketoprofen and Mefenamic Acid is small (6 and 14 doctors respectively) the differences are probably not significant.

**Table 4.15a      Duplication for Brands  
12 weeks            and Generics**

Prescribers of:	Who also prescribe:	
Adalat Nifedipine	Ada Nif 17	8
Average	44	17

Prescribers of:	Who also prescribe:	
Feldene Piroxicam	Fel Pir 24	3
Average	51	13

Prescribers of:	Who also prescribe:	
Indocid Indomethacin	Ind Ing 23	10
Average	39	24

Prescribers of:	Who also prescribe:	
Tenormin Atenolol	Ten Ate 31	24
Average	49	30

Prescribers of:	Who also prescribe:	
Inderal Propranolol	Inr Pro 25	22
Average	33	23

**Table 4.15b Duplication for brands and generics**  
12 weeks

Prescribers of:	Who also prescribe:	
Frumil Frusemide	Fru Frg 26	36
Average	28	35

Prescribers of:	Who also prescribe:	
Brufen Ibuprofen	Bru Ibu 56	20
Average	60	26

**Table 4.15c Duplication for brands and generics**  
12 weeks

Prescribers of:	Who also prescribe:	
Ponstan Mefenamic Acid	Pon Mef 50	4
Average	33	3

Prescribers of:	Who also prescribe:	
Oruvail Ketoprofen	Oru Ket 43	8
Average	34	8

It seems therefore that while there is a tendency for some doctors to favour the brand or the generic version of an entity, it is important to recognise that it is not an exclusive partition and that the strength of the effect varies across the entities in the two product markets.

Further research would be necessary to investigate whether the effect itself was a permanent feature of the market and also whether or not the variability across entities changed. Only then would it be possible to start to understand why such patterns exist.

The extent of the partitioning can be seen by looking at the number associated with Adalat and Nifedipine in the quarter. Of the 78 doctors who prescribed Adalat, 6 also prescribed Nifedipine versus the 13 expected.

#### **4.10 Conclusions**

There are a number of robust patterns in the way that prescription pharmaceuticals are prescribed: Double Jeopardy, Natural Monopoly, distribution of prescription frequency, and lack of segmentation in terms of duplication of prescription. These patterns are well established and have been found in numerous other markets. In addition, in the case of the musculo-skeletal product field, the high variability of prescription frequency compared to penetration has been noted. Also, the duplication patterns between similar or identical entities with different names have been explored.

In practical marketing terms, this chapter has concluded that when faced with the choice of marketing the same chemical entity in different strengths using either the same name or different but related names, there appears to be no disadvantage to following the latter course as long as the incremental marketing costs are minimal.

There appears to be no grounds for developing a hybrid entity in order to appeal to a specific group of doctors who are already using one of the active ingredients. Such development should be based solely on general market need and promoted to all doctors.

The tendency for doctors to favour a brand over its generic equivalent (or vice versa) exists for some entities. Tracking such trends through the life of an entity while it remains on patent could help the marketing manager to plan the post-patent life of the entity. For example, if the levels of duplication between brand and generic remain low and the share of generic prescribing stays low, then one might conclude that it is sensible to carry on marketing the brand albeit in a different way following new competition from generics (eg the case of Ponstan above). If, however, the levels of duplication are high and the share of generics is also high then an appropriate course of action might be to delete the brand from the prescription only market and launch a generic equivalent as in the case of Frumil above.

Given the familiar patterns inherent in these data and the fact that a theory has already been developed which explains such patterns, it seems sensible to use existing theory to further explore the way that doctors prescribe drugs.

The sensible course of action is, therefore, to test these data against the established theory.

In **Chapter 5** Dirichlet theory is introduced, and it is then applied to the prescribing data in **Chapters 6-8**.

## **CHAPTER 5: THE DIRICHLET MODEL**

### **5.1 Introduction**

### **5.2 Purchase Incidence**

5.2a Poisson Assumption of Individual Behaviour

5.2b Gamma Assumption of Population Variability

### **5.3 Brand Choice**

5.3a The Multinomial Assumption of Individual Choice

5.3b The Dirichlet Distribution of Population  
Variability

### **5.4 The NBD-Dirichlet**

### **5.5 Operationalising the Model**

### **5.6 Limitations of the Dirichlet**

5.6a Stationarity

5.6b Explanatory Variables

5.6c Evaluating the Incorporation  
of Explanatory Variables

### **5.7 Summary**

### 5.1 Introduction

This chapter describes the Dirichlet model and the assumptions which underlie it. The aim of the chapter is to show why it is a good model to use rather than to derive the formulae for operationalising the model. The mathematical derivation can be found in Ehrenberg (1988) which is a slightly revised version of Goodhardt, Ehrenberg and Chatfield (1984).

The model consists of two parts, one concerning purchase incidence and the other brand choice. Each part can be further divided into one element concerning how individual behaviour can be represented and another which describes how individual behaviours vary across the population. The Dirichlet is formed from a mixture of these four elements which can each be represented as distributions, along with one further assumption about the relationship between purchase incidence and brand choice.

While each of the five elements which comprise the Dirichlet has a sound theoretical basis which in turn provides a rationale for the model, the more practical justification for its adoption is the wide range of close predictions the model makes about how brands are purchased in an extensive diversity of marketing situations (Ehrenberg, 1988).

The Dirichlet does not predict the behaviour of individuals, but yields probabilistic aggregate measures across buyers which are of direct relevance to practitioners. This is because the purchasing patterns of individuals appear sufficiently irregular so that in aggregate they can be summarised by a probabilistic model. This means that consumer behaviour is measured by how the market buys each of the available offerings, so that the unit of analysis becomes the brand. Such a formulation is of direct relevance to managers as most markets comprise a very large number of buyers, and measuring individual behaviour would not be of practical use in any case.

The Dirichlet assumptions strictly apply to stationary non-segmented markets. In practice, these constraints have not proved problematic because most fast moving consumer goods markets are well established (ie not growing) and show little overall sales trend in time periods between about a week and year. In addition, most fmcg markets are characterised by brands which tend to appeal to every consumer rather than an identifiable sub-set. Furthermore, most Dirichlet-type patterns continue to hold approximately, even in more or less dynamic markets.

**Section 5.2** explains the part of the model which describes purchase incidence and **Section 5.3** repeats the process for brand choice. **Section 5.4** looks at the complete model and **Section 5.5** describes the process of operationalising the model. **Section 5.6** examines some criticisms of Dirichlet modelling and evaluates the extension of the model to incorporate explanatory variables. The chapter concludes with a brief summary.

## **5.2 Purchase Incidence**

This section looks at assumptions about individual purchase incidence and then how this varies across the population.

### **5.2a Poisson Assumption of Individual Behaviour**

The Dirichlet assumes that each consumer buys in a way which can be modelled as a Poisson process (see for example Ehrenberg, 1959, 1972). The strict theoretical conditions for this to hold are two-fold:

1. That the consumer will buy a brand or a product class with a certain fixed probability in a given time period.
2. That the probability of making a purchase does not depend on precisely when the previous purchase was made.

This means firstly that purchase behaviour can be modelled as a random process where knowledge of the last purchase does not help to predict the next incidence.

This assumption of randomness is open to question in that there may be items which are consumed regularly and are therefore purchased in a more regular pattern than that implied by a Poisson process. An example might be newspaper or magazine subscription. Here the purchase occasion would be the act of subscription not the delivery of the individual paper, whereas purchases made from news stands are almost certain to be Poisson-like. More generally, a more 'regular' purchase would merely result in a higher mean with the precise timing of each purchase still varying irregularly.

Secondly, if a consumer has just made a purchase of a particular product, it seems reasonable to assume that they are less likely to buy it again at the next shopping trip (let alone in the next hour), than if a period of time has elapsed which means the first purchase has been used up.

A number of researchers have used alternative distributions to try and capture such effects (see for example Herniter, 1971; Chatfield and Goodhardt, 1973; Banerjee and Bhattacharyya, 1976; Zufryden, 1978; Jeuland, Bass and Wright, 1980; Lawrence, 1980; Sichel, 1982 and Gupta, 1988). In practice, these modifications do not seem to improve the fit with actual sales data sufficiently (if at all) to warrant the added complexity when compared with the simple exponential form (Chatfield and Goodhardt, 1973).

One reason why the Poisson provides a good model for purchase incidence is the length of the analysis period used in practice. In general, marketers are interested in sales trends in the medium term such as a month or a quarter. These are long in relation to the average potential inter-purchase time which, for most people, equates to the weekly supermarket trip.

In the case of the current research, the Poisson assumption seems likely to be an even closer approximation than in the case of grocery purchases. As the data is concerned only with new and changes of prescription, there are no obvious reasons for regularity in prescribing. In addition, there is in principle no reason why a decision to write a prescription would be influenced by anything other than patient need which will be independent of the previous prescription occasion. An individual doctor's tendency to prescribe given the vast array of circumstances encountered would be represented by the Poisson mean for that doctor.

Unlike most household purchasers, doctors also prescribe many times each day and therefore analysis periods of a month or a quarter are significantly longer than the inter-purchase times found in grocery markets.

#### 5.2b Gamma Assumption of Population Variability

The second element of modelling purchase incidence reflects the fact (directly observable from consumer panel data) that individual consumers differ consistently in the rates with which they buy a product class. In other words, a product market is comprised of consumers whose average rates of purchase can be modelled by Poissons with different means. The purchase incidence part of the Dirichlet model assumes that these mean rates of purchase are distributed over the population according to a Gamma distribution.

The Gamma distribution has been derived from the assumptions that a consumer buys the product class at a rate independent of each of the other product classes, and the proportion of purchases which a product class accounts for is independent of the total of all purchases made. From these assumptions it has been demonstrated (Goodhardt and Chatfield, 1973; Chatfield,

1975) that the distribution of the mean rates of purchase for the product class across the population must be Gamma. It should be noted that there is so far little direct evidence to support this derivation but it is known to apply empirically to brands within a product class, (Ehrenberg, 1988) and also shown by the results in **Section 6.5**.

In the case of the current research, there is some direct evidence to support the Gamma assumption. In **Section 3.3** low correlations of prescription rates were shown for product classes and the diagnostic sub-categories as well as for heavy, medium and light prescribers.

Combining the means of the individual Poissons according to a Gamma distribution results in a Negative Binomial Distribution of the frequencies with which the population buys the product class. This distribution has been fitted to many consumer product classes at the total and the individual brand level (Ehrenberg, 1988). It is consistent with the empirical patterns of prescribing described in **Section 4.4** and the model predictions are compared with the observed distributions in **Section 6.2**.

The purchase incidence part of the Dirichlet is summarised in Table 5.1 which is based upon the same data from which Table 3.9 was derived.

The long run averages in Table 5.1 illustrate that the average 'sessional' prescribing rates are close to, but different from the long run Poisson means for each individual doctor. These figures also show that while rare events are not necessarily relevant as proof of a Poisson process, prescribing for Arrythmia is in fact a rare event.

Table 5.1 A Stochastic Model over Time Yielding the NBD

Arrhythmia Diagnosis Category					
	No. of prescriptions in:			Long-run Averages*	Distributions (horizontally)
	First 24 wk	Second 24 wk	Whole Year		
Doctor					
1	16	14	30	$\mu_1 = .120$	Poisson
2	11	9	20	$\mu_2 = .092$	Poisson
3	6	9	15	$\mu_3 = .059$	Poisson
4	7	7	14	$\mu_4 = .055$	Poisson
5	6	6	12	$\mu_5 = .050$	Poisson
6	6	5	11	$\mu_6 = .045$	Poisson
7	3	7	10	$\mu_7 = .041$	Poisson
8	1	4	5	$\mu_8 = .020$	Poisson
9	2	2	4	$\mu_9 = .021$	Poisson
10	2	2	4	$\mu_{10} = .018$	Poisson
etc					
Total	382	396	778		
Mean	m/2	m/2	m	m	
Distrib. (vertic)	NBD	NBD	NBD	Gamma	

\*Assuming a doctor takes (say) 250 surgery sessions per year.

Note: 82 of the 243 doctors did not write a prescription for this diagnosis during the year

A direct test of the Poisson assumption is strictly speaking infeasible because individual long run average purchase rates cannot be directly observed. In the current research however, the musculo-skeletal product class is very frequently prescribed by many doctors, and therefore the monthly data could approximate a long run Poisson mean. This was tested using the same set of entities used in model fitting in the second part of Chapter 6. They were analysed on a monthly basis for all doctors to derive the Poisson Index of Dispersion (P.I.D) (Kendall and Stewart, 1967) for each entity which is calculated as follows:

$$P.I.D. = \Sigma \frac{(x_i - x_{av})^2}{x_{av}}$$

For monthly data, the P.I.D. should lie between 3.8 and 21.9 to be consistent with a Poisson process. Table 5.2 shows the percentage of doctors for whom this was found to hold.

**Table 5.2 Percentage of Doctors where Prescribing Pattern was Consistent with a Poisson Process Musculo-skeletal**

Monthly data	Total %
Ibuprofen	74
Naproxen	75
Coproxamolc	90
Paracodeine	81
Voltaren	79
Indomethacin	84
Piroxicam	79
Mefenamic	78
Ketoprofen	77
Average	80

In most cases then, prescribing behaviour is consistent with the assumption of a Poisson process. For the inconsistent doctors it is likely that the data is insufficient to approximate the long run mean rate of prescription. This does not, of course, invalidate using the Poisson assumption, given the traditional indirect test of effectively fitting an NBD to the individual entity and product class data (see Section 6.2).

In the current research and for the first time, however, some direct evidence to support a Poisson process is presented.

### 5.3 Brand Choice

As in the previous section the assumptions surrounding individual choice will be described and then how these choices vary across the population.

#### 5.3a The Multinomial Assumption of Individual Choice

The Dirichlet assumes that each time a consumer makes a purchase s/he has a certain probability of choosing each of the available brands. These probabilities are fixed over time and sum to 1 because by definition a purchase is made. Each consumer has a set of probabilities represented by a multinomial process akin to throwing a weighted dice. Here the probability of getting a particular score is constant each time the dice is thrown, but a different result can occur. Like the throw of the dice, where the results of successive throws are independent, the brand chosen is independent of previous choices.

The first part of this brand choice assumption is borne out by actual consumer data, where the various brands purchased by consumers have differing shares of the consumer's total purchases (see for example Wellan, 1985). As overall brand shares are effectively constant, this supports a model with fixed probabilities.

#### 5.3b The Dirichlet Distribution of Population

##### Variability

Just as each consumer has a different purchase incidence probability, they also have differing sets of brand choice probabilities. For any one brand, this variation in probabilities is assumed to follow a Beta distribution and the model assumes that the Beta distributions for each brand combine in the form of a particular multivariate Beta distribution known as the Dirichlet.

A key prediction from a Dirichlet formulation is that the choice between brands should be independent, which is what is meant when describing a market as unsegmented. There is a strong parallel here with the Independence of Irrelevant Alternatives assumption of Luce (1959) which is a key concern when modelling choice processes as a Logit, (see for example Jain and Bass, 1989).

Essentially there is a concern that these independence assumptions will not hold when the consumer is faced with choices which are asymmetric in terms of similarity. In a hypothetical market with two brands of carbonated soft drink, one orange and another cola flavoured, independence may be assumed. If a second cola brand was launched, the independence assumption would predict that the market shares of the original brands would change by the same amount. It is reasonable to expect, however, that the share of the original cola would fall by a greater amount as it would be more similar to the new brand than the original orange flavoured drink.

In practice, the validity of the Dirichlet and its independence assumption are tested by how well it actually models and predicts both brand choice and purchase incidence. Where deviations from the model occur it is easy (unlike Logit modelling) to examine individual brand data on, for example, duplications to explore reasons why the model does not provide a good fit. This form of analysis also helps to identify the existence of sub-markets or partitioning effects, such as the families-with-children segment in the breakfast cereal market, and it also facilitates evaluation of the size of the effect which tends to be relatively small. In addition, because of the formulation of the Dirichlet, it is possible to combine brands which appear to violate the independence assumption in order to see whether the lack of fit is specific or more fundamental.

The brand choice elements of the model can be summarised by table 5.3. which is also based upon table 3.9.

**Table 5.3 A Stochastic Model over Brands  
Yielding the Dirichlet**

<u>Arrythmia Diagnosis Category</u> <u>Prescribing of Entities in a Year:</u>						
	Entity:					Long-run Distributions. (horizontally)
	A	B	C	D	E	
Doctor						
1	7	3	1	13	6	multinomial
2	5		14		1	multinomial
3	8			5	2	multinomial
4	2	1	7	2	2	multinomial
5	1		7	1	3	multinomial
6	7		1	1	2	multinomial
7	6		2		2	multinomial
8	2		2		1	multinomial
9	2		1	1		multinomial
10	2		2			multinomial
etc						
Distrib. (vertic)	$\beta$	$\beta$	$\beta$	$\beta$	$\beta$	Dirichlet

Note: The numbers in the table are the observed data for the prescriptions written for Arrythmia in the year for a sample of 10 of the 161 doctors who prescribed. They are used to illustrate the variability across doctors.

#### 5.4 The NBD-Dirichlet

One further assumption needs to be stated before the overall model can be specified and that is that the brand choice and purchase incidence probabilities of consumers are distributed independently over the population.

In practice this means that brand shares should be effectively constant across different groups of consumers and table 3.18 provides some evidence for this at the diagnosis level.

A characterisation of the complete model is shown in table 5.4 using data from the Arrythmia cardiovascular diagnosis.

**Table 5.4. A Stochastic Model Over Brands  
Yielding the NBD-Dirichlet**

<u>Arrhythmia Diagnosis Category</u> <u>Proportions Devoted to Each Entity in a Year:</u>						
	Entity:					Long-run Dist.
	A	B	C	D	E	Total (horiz.)
Doctor						
1	.23	.10	.03	.43	.20	30 multinomial
2	.25		.70		.05	20 multinomial
3	.53			.33	.13	15 multinomial
4	.14	.07	.50	.14	.14	14 multinomial
5	.08		.58	.08	.25	12 multinomial
6	.64		.09	.09	.18	11 multinomial
7	.60		.20		.20	10 multinomial
8	.40		.40		.20	5 multinomial
9	.50		.25	.25		4 multinomial
10	.50		.50			4 multinomial
etc						
Distrib. (vertic)	$\beta$	$\beta$	$\beta$	$\beta$	$\beta$	NBD Dirichlet

Table 5.4 illustrates the importance of considering purchase incidence as well as brand choice. If, for example, the data were an accurate representation of the long run multinomials of each doctor, one would have doctor 10 choosing entity A with a probability of 0.5 and the first doctor choosing A with a probability of 0.23. Because doctor 10 is a very light prescriber only two prescriptions result whereas the lower choice probability of the first doctor results in seven prescriptions of entity A.

### 5.5 Operationalising the Model

A detailed worked example of the calculations necessary for producing theoretical Dirichlet output is found in appendix C of Ehrenberg, 1988 and in practice the calculations are effected most easily using the BUYER software (Uncles, 1989).

In essence the procedure uses three stages.

Firstly, the purchase incidence NBD is calculated, and the sole inputs here are the number of buyers in the time period and the total number of purchases made. From these two figures the proportion of non-buyers ( $p_0$ ) and the average rate of purchase ( $m$ ) are easily calculated and the exponent of the NBD ( $k$ ) is subsequently calculated by iteration using the identity:

$$p_0 = (1+m/k)^{-k}$$

From here the proportion buying any number of times is quite easily computed using the iterative formula (starting with the observed value of  $p_0$ ) as follows:

$$p_r = (a/1+a) \times [1-(a-m)/ar] P_{r-1}$$

where  $a=m/k$ .

The nature of the distribution means that the tail can represent a very small proportion of buyers who buy very heavily and are therefore important in sales terms. A good practical example is found in Ehrenberg (1988, p. 360) where one buyer makes 20% of the total purchases for the product class. In modelling purchase behaviour it is important to evaluate this tail which can be estimated using Goodhardt's method as described in Ehrenberg (1988, pp. 339-340). An example of doctors prescribing for Arrythmia is provided later in this section.

The second stage involves the calculation of the Dirichlet 'S' parameter for each item in the analysis. This parameter reflects the heterogeneity of consumers in terms of their choice probabilities and is derived using the previously computed purchase distribution along with the proportion not buying the item in the time period, the average item purchase frequency and the average product class purchase frequency.

The objective is to find an estimate of the S parameter for each brand so that the predicted number of non-buyers of the brand is very close to the observed number of non-buyers. This is achieved by starting with an arbitrary value for S and generating two computational terms which aid the recursive calculation encompassing the length of the product class distribution. Once the recursive calculation has been made up to the end of the distribution, the resulting estimated proportion of non-buyers is compared to the observed value. If the estimate exceeds the observation, the process is repeated using a larger starting value for S (and vice versa). This process continues until a value of S is found which provides a close fit between the estimate and the observation (a detailed worked example is provided in Ehrenberg, 1988, pp 342-344).

The estimation is most easily accomplished by a computer using software such as BUYER (Uncles, 1989), which generates a value for each item. The S parameter for the product class is then derived by multiplying the S parameter of each item by its market share and summing over the number of items.

The third stage is to derive a matrix of proportions for each item in the analysis. This matrix shows what proportion of buyers who make n product class purchases choose the specific item 0,1,2,...n times.

To illustrate the procedure, data for the first 24 weeks of 1986 for the Arrhythmia diagnosis together with the data for Propranolol (entity C in tables 3.9, 5.3 and 5.4) are used. The relevant inputs into the model are summarised in table 5.5.

**Table 5.5 Input Data for Dirichlet Predictions for Propranolol Prescribing for Arrhythmia in 6 Months**

Sample size	243
Number of doctors prescribing for Arrhythmia	127
Total Number of prescriptions written	382
Number of prescriptions for Propranolol	45
Proportion Prescribing for Arrhythmia (B)	.52
No. of Arrhythmia Prescriptions per Prescriber (W)	3.01
No. of Arrhythmia Prescriptions per Doctor (M)	1.57

These inputs provide the parameters for the model which are listed in table 5.6.

**Table 5.6 Parameters for Dirichlet Predictions for Propranolol**

Arrhythmia
m = 1.5730
k = 0.5439
a = 2.8923
S = 1.5546
Propranolol
$\alpha = 0.1834$
$\beta = 1.3712$

The proportion of doctors  $P_n$  who write  $n$  prescriptions for Arrhythmia is given by:

$$P_n = [a/(1+a)] [1-(a-m)/an] P_{n-1}$$

Using  $P_0 = 1-B = 0.48$  (or 0.4774 to be precise) this recursive formula produces the proportions listed in the first row of figure 5.1. The cumulative proportion of doctors who prescribe up to and including 12 times is 99.29% and these doctors account for 1.466 out of the 1.573 for the overall average prescription frequency (m).

Goodhardt's method for calculating the tail of the distribution proceeds as follows:

$$\begin{aligned}
 P_R &= 1 - .9929 &= &.0071 \\
 Q_R &= 1.573 - 1.466 &= &.1070 \\
 Q_R/P_R &&= &15.0704 \text{ so } n' = 15 \\
 P_{n'+1} &&= &P_{16} = .0071 \times .0704 = .0005 \\
 P_{n'} &&= &P_{15} = .0071 - .0005 = .0066
 \end{aligned}$$

The first row of table 5.5 is used to derive the proportion of doctors who write no prescriptions of Propranolol and  $n$  prescriptions for Arrythmia using the following formula

$$P_{0n} = P_{0(n-1)} \times (\beta + n - 1) / (\alpha + \beta + n - 1) \times P_n / P_{(n-1)}$$

The remaining entries for table 5.5 are found from the recurrence formula

$$P_{rn} = (n - r + 1) / r \times (\alpha + r - 1) / (\beta + n - r) \times P_{(r-1)n}$$

**Figure 5.1 Dirichlet Matrix of Proportions for Arrythmia and Propranolol.**

Number	Prescriptions for Arrythmia - 24 weeks																Total	
	0	1	2	3	4	5	6	7	8	9	10	11	12	15	16			
Proportions	0.4774	0.1702	0.0906	0.0541	0.0342	0.0223	0.0149	0.0101	0.0069	0.0046	0.0033	0.0023	0.0016	0.0041	0.0003	0.0003	0.8973	
1		0.0228	0.0140	0.0088	0.0057	0.0038	0.0026	0.0018	0.0012	0.0008	0.0006	0.0004	0.0003	0.0007	0.0001	0.0001	0.0637	
2			0.0060	0.0044	0.0030	0.0021	0.0014	0.0010	0.0007	0.0005	0.0003	0.0002	0.0002	0.0004	0.0000	0.0000	0.0203	
3				0.0023	0.0019	0.0013	0.0009	0.0007	0.0005	0.0003	0.0002	0.0002	0.0001	0.0003	0.0000	0.0000	0.0006	
4					0.0011	0.0009	0.0007	0.0005	0.0003	0.0002	0.0002	0.0001	0.0001	0.0002	0.0000	0.0000	0.0044	
5						0.0005	0.0005	0.0004	0.0003	0.0002	0.0001	0.0001	0.0001	0.0002	0.0000	0.0002	0.0023	
Prescriptions							0.0003	0.0003	0.0002	0.0002	0.0001	0.0001	0.0001	0.0001	0.0002	0.0000	0.0013	
6								0.0002	0.0002	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0000	0.0008	
7									0.0001	0.0001	0.0001	0.0001	0.0000	0.0001	0.0000	0.0000	0.0005	
8										0.0001	0.0001	0.0000	0.0000	0.0001	0.0000	0.0000	0.0003	
9											0.0001	0.0000	0.0000	0.0001	0.0000	0.0000	0.0002	
10												0.0000	0.0000	0.0000	0.0001	0.0000	0.0001	
Prescriptions													0.0000	0.0001	0.0000	0.0000	0.0001	
11														0.0000	0.0001	0.0000	0.0001	
12															0.0000	0.0000	0.0001	
15																0.0000	0.0000	
16																	0.0000	0.0000

From this matrix, together with the prior variables the following output can be simply derived:

1. The Dirichlet predicts that Propranolol will be prescribed by:  $1 - 0.8973 = 10.3\%$  of doctors.
2. The average prescription frequency for Propranolol is predicted as  $0.1849 / .103 = 1.8$ .
3. The frequency of purchasing the product class is calculated by subtracting the proportion of doctors who did not prescribe Propranolol from the proportion who prescribed for Arrythmia  $n$  times, multiplying by  $n$  and summing over  $n=1...16$ . This is calculated as 3.96 and means that on average Propranolol accounts for just under half of its prescribers requirements in a half-year.
4. The proportion of sole buyers is easily calculated by summing the diagonal entries (excluding the non-prescribers) = 3.3%.
5. The sole buying purchase frequency is also calculated from the diagonal data as 1.6.

Other multi-brand data is also produced by the model including:

6. The proportion of buyers who buy any two brands.
7. The frequency of purchase of duplicate buyers.
8. The average number of brands purchased per buyer.
9. All of the above in differing time periods.

These theoretical calculations can be compared with tabulations from panel data in order to validate the use of the model with a specific data set and also to expose specific instances where consumer behaviour deviates from the assumptions which underlie the model.

As a simple check, table 5.7 summarises some of the Dirichlet predictions for Propranolol prescribed for Arrythmia in the first half of 1986 along with the observed data.

**Table 5.7 Observed and Theoretical Prescribing Measures Propranolol**

	Obs	Dir*
Penetration (b)	9.9%	10.3%
Prescription Frequency (w)	1.9	1.8
Product Usage (wp)	4.4	3.9
Proportion of Sole Prescribers (bs)	2.9%	3.3%
Frequency of Sole Prescribers (ws)	1.1	1.6

\* Obs = Observed data, Dir = Dirichlet Prediction.

It can be seen that the Dirichlet provides a good estimate of the observed measures of prescribing behaviour in this case. **Chapters 6-8** provide more general and wide-ranging examples of the Dirichlet's predictive abilities.

In summary, the Dirichlet model uses market shares to generate a whole series of predictive norms about the way in which consumers buy the available brands in a product market. These predictions can be compared with actual brand performance so that analysis can focus on deviations from the established norms.

### **5.6 Limitations of the Dirichlet**

The key assumptions of stationarity and lack of market segmentation encounter resistance in the eyes of practitioners, many of whom see increasing sales and loyalty as key elements of their marketing plans. The tools available to the marketer are not represented as parameters of the Dirichlet and this in part has led to the strand of Marketing Science which uses a Logistic regression approach which incorporates 'explanatory' variables such as discounting and promotional activities (see **Chapter 1**).

### 5.6a Stationarity

While the Dirichlet is based strictly upon the stationarity assumption, it does not need to be discarded in cases where individual brands experience changes in sales levels. Most branded f.m.c.g markets are characterised by wide ranging promotional activities which essentially provide the consumer with some short term 'extra value'. Such promotions tend to last for relatively short periods when compared to the annual benchmark of relative brand performance. Marketers should be interested in knowing the effect of promotional activities (and those of competitors), in terms of how consumer behaviour changes during and after the promotion. Here the Dirichlet can be used to compare the before, during and post promotional phases to examine whether or not any sales increase derives from more buyers than expected or from increased usage by the expected number of buyers.

Promotional effects will make the sales of a brand appear non-stationary in the short term, but even if the Dirichlet predictions for the promoted brand are affected, it does not preclude its use on the rest of the market. Consider a twenty brand product market and a brand which increases its sales from a 10% to a 15% share (an increase of 50%) during a promotion. Whereas before the promotion the remaining 19 brands held a combined share of 90%, during the promotion this would fall to 85%, but the difference would be 0.2% per brand, and this would hardly affect the Dirichlet predictions. A marked example of this phenomenon is found in the current research where one cardiovascular entity, Capoten, fails to fit the Dirichlet predictions. The model is still used to good effect with the other entities in the market, and the predictions help to analyse the possible reasons for the atypical patterns found (see Chapter 9).

If a market is shown to be non-stationary in the longer run, then the Dirichlet can still be used to provide approximate measures of buyer behaviour, with consistent discrepancies showing up and highlighting the areas for further analysis. A more complex approach is typified by Fader and Lattin (1992) who attempt to incorporate non-stationarity into a Dirichlet-type modelling process. The authors do not, however, provide operational measures to evaluate the effectiveness of the model which in any case can only be applied retrospectively.

#### 5.6b Explanatory Variables

While there has been a plethora of different Logit type models specified in the literature it is only recently that Fader (1993) attempted to incorporate explanatory variables into a Dirichlet type model.

Fader concluded that incorporating data on brand display and prices did improve the model fit when compared to a 'pure' Dirichlet

'It should come as no surprise that the pure DM (Dirichlet Multinomial) fits notably worse than the two models with explanatory variables. On the other hand it is interesting that the incremental improvements in moving away from the pure DM model are rather modest' (Fader 1993, p. 105).

Fader's measure of fit is rho-squared, but its meaning is not defined and so it is hard to quantify the model comparison which is made.

In his paper, Fader does not provide the summary statistics of penetration and purchase frequency, but does report the S parameters for both models. From these it is possible to examine the performance of both models by comparing observed with predicted market shares.

In all except the case of the store brand, the 'pure' Dirichlet provides as good if not better predictions than the model which incorporates marketing mix

variables. As Fader points out, the main reason for this discrepancy will lie in the store brand's limited distribution.

The easiest way of dealing with such a problem is to leave the store brand out of the estimation procedure and then check the fit with the other brands in the market to see whether the problem is general or specific. If it is found to be specific to the store brand but that the pattern is one generally found in grocery markets for all individual store brands, then the analysis needs to incorporate such a finding.

Ellis (1989) examined this problem and concluded that overall, store brands showed a small but consistent deviation from Dirichlet predictions which could be resolved by either correcting for limited distribution or by combining all own labels into a single entity.

#### 5.6c Evaluating the Incorporation of Explanatory Variables

In essence, Fader demonstrates how the incorporation of explanatory variables changes the Dirichlet brand parameters. In order to evaluate the impact of Fader's result, simulations were run which measured changes to the Dirichlet S parameter based upon prescribing data for 1 week in 1986. The data are extracted from table 6.2 and were chosen to provide entities with similar market shares to the brand leader, the store brand and the smallest brand in Fader's orange juice category.

Three sets of simulations were run on the assumption of a two entity market. The first used 'Other' with a share of 32% and 'the rest' with a share of 68%. The second used Naproxen, and the third used Mefenamic Acid from table 5.8, which also shows the shares of three of the orange juice brands used by Fader.

**Table 5.8 Prescribing of Three Musculo-skeletal in a Week and Market Shares from Fader (1993)**

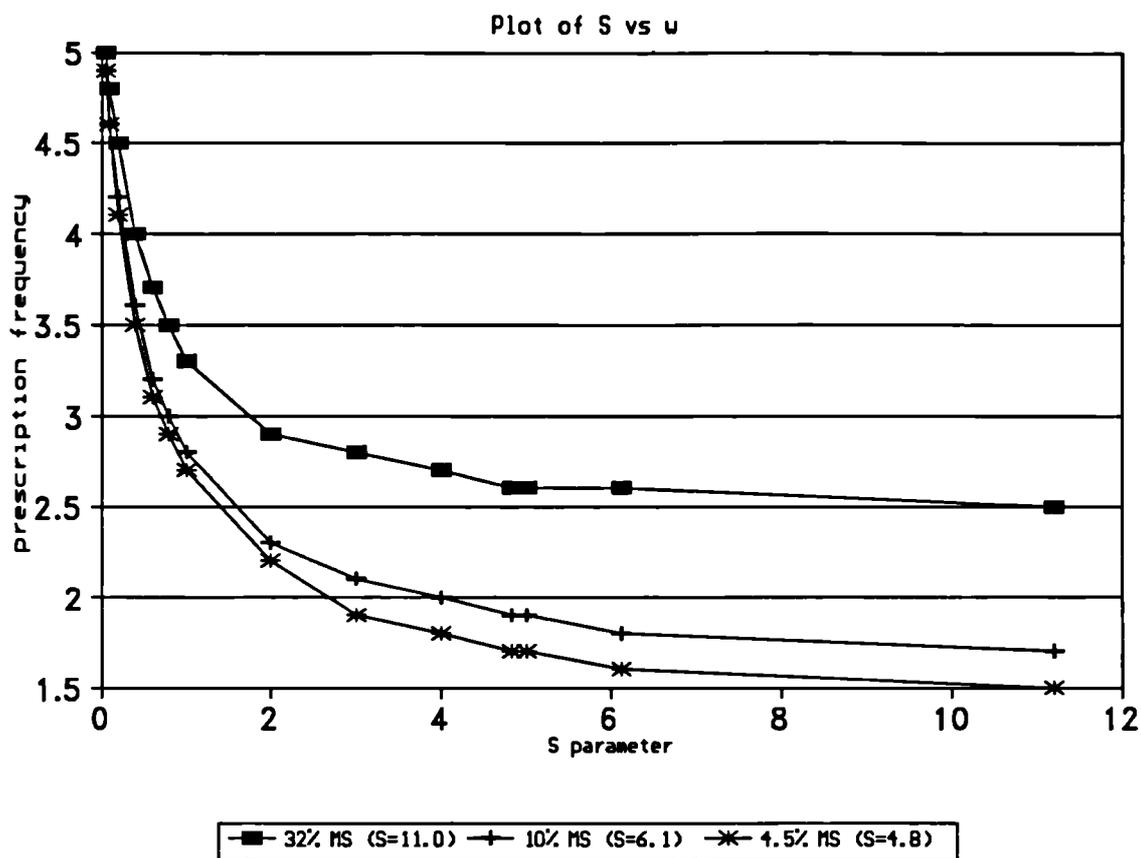
Entity	Market Share %	Proportion of doctors Prescribing(%)	Average Prescription Frequency
Other	32.1	53.9	2.5
Naproxen	10.0	23.4	1.8
Mefenamic	4.5	21.3	1.7
Citrus Hill	28.8		
Store Brand	13.7		
Tropicana P	4.2		

For each of the first three entities in table 5.8, simulations were run as if the market consisted of that entity and 'all other entities combined'. The data on penetration and prescription frequency was entered into the BUYER software (Uncles, 1989) and kept constant while seven runs on each entity were made using different values of the S parameter. The results of these simulations are found in table 5.9. It can be seen that in terms of output, the Dirichlet is not very sensitive to changes in the S parameter, and also that when the S parameter falls below 0.1, the prescription frequencies tend to be around 5 irrespective of the entity market share. This pattern is shown in figure 5.2, along with the actual values for the S parameter in the three cases.

**Table 5.9 Variation of Penetration and Purchase Frequency with S and Market Share.**

S	MS=32%		MS=10%		MS=4.5%	
	b	w	b	w	b	w
5	51.2	2.6	22.4	1.9	11.1	1.7
3	48.5	2.8	20.2	2.1	9.8	1.9
1	40.4	3.3	15.0	2.8	7.0	2.7
0.8	38.7	3.5	14.1	3.0	6.5	2.9
0.4	33.8	4.0	11.7	3.6	5.3	3.5
0.1	28.1	4.8	9.1	4.6	4.1	4.6
0.05	26.8	5.0	8.5	4.9	3.8	4.9

**Figure 5.2 Plot of the Dirichlet S Parameter against Prescription Frequency**



The brand parameters from table 1 of Fader (1993) are divided by the actual brand shares to derive the individual S parameters which are shown in table 5.10

**Table 5.10 Comparison of Fader's Models**

Brand	Market Share (%) Observed	S Parameters	
		Dir	MNL-Dir
Citrus Hill	28.8	3.6	4.6
Minute Maid	17.0	3.0	4.9
Regional Brand	15.1	3.6	2.7
Tropicana Regular	14.6	4.1	3.1
Store Brand	13.7	8.5	1.9
Tropicana Premium	4.2	1.8	5.2

The changes in S parameter when moving to the Multinomial Logit - Dirichlet Hybrid are small for the biggest brands in the market. The differences when expressed in measurable terms such as the number of

buyers and average frequency of purchase will be very small indeed. For the brand leader, the purchase frequency would fall by about 4% and the penetration rise by about 4% (interpolated from figure 5.2) - hardly significant improvements given the added complexity of the model.

The most significant differences occur for the Store Brand and Tropicana Premium. In the first instance, limited distribution and the population at risk probably account for most of the difference, and Tropicana Premium is a small brand. As figure 5.2 shows, even the shift in S parameter from 2 to 5 will have a very small impact on the number of buyers and their frequency of purchase.

This analysis demonstrates that incorporating explanatory variables may improve the statistical fit with a single data set, but adds little to understanding the market structure in terms of how brands are purchased - variables of relevance to marketing practitioners. The same is probably true for the potential to incorporate non-stationarity into the analysis with far greater insights deriving from analysis of deviations from the 'pure' Dirichlet predictions.

### **5.7 Summary**

The Dirichlet is a comprehensive model which describes the structure of buying behaviour in terms of purchase incidence and brand choice under stationary (or near stationary) situations. The stochastic properties of the model (which is driven by market shares) incorporate the results of past marketing actions, and this helps to explain why efforts to account for explanatory variables are unlikely to prove as productive.

Where some component of the market exhibits a dynamic (as opposed to a stationary) pattern, this can be analysed separately against the Dirichlet norms.

The output of Dirichlet modelling includes measures which are of direct relevance to practitioners, and helps to compare a brand's performance with others in the market as well as with a set of norms which have an empirical and a theoretical basis. This means that marketers can plan from a knowledge of what the market is actually like, to see whether or not their goals are in fact realisable.

The applicability of the Dirichlet to physician prescribing will now be examined in detail.

**CHAPTER 6: THE FIT OF THE NBD-DIRICHLET AT THE  
PRODUCT CLASS LEVEL**

**Overview**

**6.1 Introduction**

**6.2 The Fit of the NBD**

**6.3 Double Jeopardy**

**6.4 Growth in Penetration and Frequency**

**6.5 Prescribing the Product Class and Natural Monopoly**

**6.6 Share of Requirements**

**6.7 Sole Prescribing**

**6.8 Duplication of Prescriptions**

**6.9 Variation in Penetration and Prescription Frequency**

**6.10 A Practical Application of the Approach**

**6.11 Conclusions**

### Overview

The NBD-Dirichlet successfully models the following patterns of prescribing behaviour, primarily under steady-state conditions:

1. The distribution of prescription frequencies for individual entities in both product fields.
2. The Double Jeopardy pattern
3. Growth in penetration and prescription frequency over time.
4. Product class prescribing rates.
5. The share of product class prescriptions accounted for by each entity.
6. The incidence and frequency of sole prescribing.
7. The general lack of market partitioning.
8. How penetration and prescription frequency vary across entities within a product class.

It also provides benchmarks for establishing departures from these patterns.

### 6.1 Introduction

In order to examine the fit of the model at the product class level, two separate analyses are conducted. Firstly, the distribution of prescription frequencies for the entities described in Chapter 4 for both product classes are compared to those predicted from the NBD part of the Dirichlet. The 10 cardiovascular entities accounted for just under 30% of the total number of prescriptions and the 10 musculo-skeletal entities accounted for about 40% of the total. This 'disaggregated' level of analysis will also be used when the

prescribing patterns for brands and their generic equivalents are examined in **Chapter 8**.

Secondly, both product fields are modelled using the composite Dirichlet. As there are over 40 different entities in each product class which are of significant size, each product class was subjected to an aggregation procedure in order to reduce the number of entities to a more manageable number which would facilitate interpretation, while at the same time accounting for a large proportion of the prescriptions written.

This process involved grouping together all chemically equivalent entities, while ensuring that entities which had significant shares within one (small) diagnostic sub-class were not aggregated (see **Chapter 7** for diagnosis entity shares). The results are shown in tables 6.1 and 6.2.

**Table 6.1 Market Shares of Aggregated Entities: Cardiovasculars**

	Total %
Atenololc	13.7
Frusamide	9.7
GTN	9.0
Nifedipine	8.8
Captopril	6.2
Propranolol	5.5
Bendrofluazide	4.7
Cyclopenthiazide	3.9
ISMO	3.1
Digoxin	2.9
Spirolactone	2.7
Bumetanide	2.4
ISDIN	2.3
Verapamilc	1.5
Other	23.8

**Table 6.2 Market Shares of Aggregated Entities: Musculo-skeletals**

	Total %
Ibuprofen	17.1
Naproxen	10.1
Coproxamol <sup>c</sup>	8.6
Paracodeine	7.2
Voltaren	6.3
Indomethacin	5.4
Piroxicam	5.3
Mefenamic	4.5
Ketoprofen	3.1
All others	32.4

In the case of the cardiovascular product field, 14 chemical entities accounted for just under 75% of all prescriptions written and the remainder all had shares of 3% or less. For musculo-skeletals, 9 chemical entities accounted for just under 70% of all prescriptions written and the remainder all had shares of less than 3%. In order to minimise problems of interpretation the letter 'c' is added to Atenolol, Verapamil and Coproxamol in this chapter to indicate where they have been subjected to this aggregation process. This explains why their market shares differ from **Chapter 4**.

**Section 6.2** uses the NBD part of the Dirichlet model to successfully model the heterogeneity which exists in prescribing behaviour. In **Section 6.3** the variability of entity penetrations and prescription frequencies are examined with a specific focus on the ability of the Dirichlet to model the empirically established Double Jeopardy pattern. **Section 6.4** looks at the Dirichlet's ability to model penetration and prescription frequency growth through time and later, **Section 6.9** combines the patterns of **Sections 6.3** and **6.4** to see how well the Dirichlet models the variability of penetration and prescription frequency within the two product classes. **Section 6.5** examines how well the Dirichlet models differences between entities in terms of the rates at which

prescribers of each entity utilise the product class. **Section 6.6** evaluates the ability of the Dirichlet to model the share of prescriptions accounted for by each entity and **Section 6.7** looks at sole prescribing incidence and frequency. In **Section 6.8** the duplications of prescription are examined and found to be largely as predicted by the Dirichlet assumptions. **Section 6.9** examines the variability of entities in terms of their penetration and prescription frequency and the ability of the Dirichlet to effectively model the resulting patterns. This analysis shows that with very frequently prescribed musculo-skeletal drugs, sales growth for the largest entities will tend to come from existing prescribers prescribing more frequently rather than from attracting more prescribers. This is a pattern which is new in empirical terms, but predicted by the Dirichlet. It thus provides a good illustration of the 'Theoretical then Empirical' part of the 'EtTtE' approach described in **Chapter 1**. **Section 6.10** gives a practical application of the approach adopted here and the chapter ends with a short concluding section.

The study of the two product classes is analogous to examining buyer behaviour in two different product fields in the grocery market which differ in their purchase frequency. One might start to generalise about prescribing behaviour if similar patterns continue to emerge in both product fields and further that these patterns are similar to those which have already been observed in other marketing situations.

### **6.2 The Fit of the NBD**

In chapter 3 the extreme heterogeneity of individual prescribers was noted for both product fields. Doctors differed in their overall rates of prescribing by a factor of 100 during a year and this could not be explained by differing practice sizes. In order to see the nature of this heterogeneity in detail, the frequencies with which individual entities were prescribed were tabulated in **Section 4.4**. Here the observed prescription distributions

are compared to those predicted by the NBD model as calculated by the BUYER computer programmes (Uncles, 1988).

Tables 6.3 and 6.4 show the observed and theoretical distributions for the same twenty individual entities which were the subject of the analysis in Section 4.4. The observed distributions of prescription were shown in tables 4.5 and 4.6. The market shares of these entities are detailed in tables 4.1 and 4.2. For cardiovasculars they range from 5% for GTNT to less than 1% for Rythmodan and for musculo-skeletal they range from 11% for Brufen to less than 1% for Prednisolone.

**Table 6.3 Distribution of Prescriptions:  
Cardiovasculars**

12 weeks		% of Doctors Writing 1,2,3,...Prescriptions								
		1	2	3	4	5	6	7	8	9+
Any	O	6	3	5	3	3	4	3	2	71
	T	4	4	4	4	4	4	4	4	67
GTNT	O	50	24	14	7	0	3	1	1	1
	T	50	24	12	7	4	2	1	1	1
Capoten	O	34	7	10	7	5	10	0	2	24
	T	33	16	10	7	6	4	3	3	17
Tenormin	O	57	22	9	5	2	3	1	0	1
	T	53	23	11	6	3	2	1	1	1
Adalat	O	54	23	14	1	3	3	1	0	1
	T	53	23	11	6	3	2	1	1	1
Atenolol	O	48	19	16	8	8	0	0	0	2
	T	50	22	12	6	4	2	1	1	1
Dyazide	O	61	27	7	2	0	2	0	0	0
	T	65	21	8	3	1	1	0	0	0
Tenoretic	O	74	12	5	10	0	0	0	0	0
	T	69	20	7	3	1	0	0	0	0
Verapamil	O	60	27	10	3	0	0	0	0	0
	T	66	21	8	3	2	1	0	0	0
Tenoret	O	60	28	8	0	0	4	0	0	0
	T	66	20	8	3	2	1	0	0	0
Rythmodan	O	78	22	0	0	0	0	0	0	0
	T	84	13	3	1	0	0	0	0	0
Average	O	58	21	9	4	2	3	0	0	3
	T	58	20	9	5	2	1	1	1	2

It can be seen from the table that the fit of the observed frequencies with those predicted by the model is excellent. The mean absolute deviation between the observed and theoretical data is under 2% in the case of cardiovascular prescribing (in table 6.3) and 2.5% in the case of musculo-skeletal (in table 6.4).

**Table 6.4 Distribution of Prescriptions:  
Musculo-skeletal**

12 weeks		% of Doctors Writing 1,2,3,...Prescriptions								
		1	2	3	4	5	6	7	8	9+
Any	O	0	0	0	0	0	0	1	0	97
	T	1	1	1	1	1	1	1	1	92
Brufen	O	15	17	8	10	7	3	2	7	32
	T	19	12	9	7	6	5	4	4	34
Coproxamol	O	25	12	9	8	4	5	6	6	26
	T	22	14	10	8	6	5	4	4	26
Naprosyn	O	24	18	6	9	7	6	3	6	22
	T	23	14	10	8	6	5	4	4	26
Feldene	O	37	17	12	5	5	5	1	3	16
	T	27	16	11	8	7	5	4	3	18
Lederfen	O	36	15	9	14	4	5	1	1	15
	T	31	17	11	8	6	5	4	3	15
Indocid R	O	44	22	8	14	2	2	0	0	9
	T	39	19	12	8	5	4	3	2	8
Benoral	O	49	11	11	6	7	4	2	0	11
	T	41	19	12	8	5	4	3	2	7
Dolobid	O	55	17	6	6	2	0	2	2	9
	T	46	21	11	7	5	3	2	1	4
Meptid	O	52	30	4	4	0	0	4	0	4
	T	50	21	11	6	4	3	2	1	3
Prednisolone	O	73	18	0	9	0	0	0	0	0
	T	69	19	7	3	1	1	0	0	0
Average	O	41	18	7	9	4	3	2	2	14
	T	37	17	10	7	5	4	3	2	14

The R squared values were calculated as 0.98 for the cardiovascular field and 0.96 for the musculo-skeletal data. The correlations were run on the 'any' and the ten entities to give 99 observations in each data set.

From a substantive point of view, the way that doctors prescribe the product class differs from the way they prescribe individual entities. This can be seen by comparing the first two rows of tables 6.3 and 6.4 with the averages at the foot of each table. In both product fields, over 70% of doctors prescribe the product 9 times or more in the quarter, whereas individual entities are in general prescribed once or twice. The distribution of prescribing the product classes is examined in more detail in table 6.5.

**Table 6.5 Distribution of Prescriptions by Category: The Two Product Classes**

12 weeks		
Number of Prescriptions	Percentage of Prescribers(%)	
<b>Musculo-skeletals</b>	<b>O</b>	<b>T</b>
1-20	13.6	24.1
21-40	26.9	25.5
41-60	28.9	18.9
61-80	12.8	12.8
81-100	9.1	8.2
101-120	4.5	5.1
121-140	1.2	3.1
140+	3.0	2.3
<b>Cardiovasculars</b>	<b>O</b>	<b>T</b>
1-10	33.9	39.8
11-20	33.5	27.7
21-30	19.0	15.6
31-40	6.3	8.2
41-50	2.5	4.0
50+	4.8	4.7

This shows that the fit of the NBD to the product class prescribing rates is good. The arbitrary categories assigned in the tables make the fit seem less impressive at first glance but if they are aggregated into broader categories equating to light, medium and heavy prescribers the resulting fit, shown in table 6.6, is excellent.

**Table 6.6 Distribution of Prescriptions by Light, Medium and Heavy Prescribers: The Two Product Classes**

12 weeks		
Number of Prescriptions	Percentage of Prescribers(%)	
<b>Musculo-skeletals</b>	<b>O</b>	<b>T</b>
Light (<61)	69.4	68.5
Medium (61-120)	27.6	29.2
Heavy (>120)	3.0	2.3
<b>Cardiovasculars</b>	<b>O</b>	<b>T</b>
Light (<21)	67.4	67.5
Medium (21-50)	27.8	27.8
Heavy (>50)	4.8	4.7

Returning to the way that doctors prescribe the individual entities, it can be seen in table 6.3 that Capoten is the main exception to the general pattern found for the other entities. The empirical differences in penetration and average purchase frequency identified for Capoten does not mean that it needs to be excluded from the analysis. While the fit is less close than for the other entities, the negative binomial is at least a fair approximation for the distribution, and there is a good reason for the deviation, which is considered in Chapter 9.

This analysis shows, therefore, that the assumptions underlying NBD theory fit the extreme heterogeneity of physician prescribing well. Indeed, if prior to this research the only available information had been aggregate data on the total number of prescriptions written along with the number of doctors prescribing, NBD theory would have predicted the patterns observed in these data.

The ability of the NBD to predict prescribing behaviour is an extreme test of the model, revealing a lot of descriptive knowledge about what doctors actually do. In addition, the results imply an underlying steady state heterogeneity where

individual doctors have very different propensities to prescribe. Of course, the model does not reveal the reason for the degree of heterogeneity seen here and this will form the basis for a future research recommendation in Chapter 12.

### 6.3 Double Jeopardy

In Section 4.1 the empirical observation was made that large entities benefited in two ways when compared to small entities. They have more prescribers and they are prescribed more frequently. Tables 6.7 and 6.8 show how the Dirichlet model recovers the observed entity penetrations and prescription frequencies, thereby also modelling the Double Jeopardy pattern.

**Table 6.7 Penetration and Prescription Frequencies for Cardiovascular (quarter)**

12 weeks	Mkt. Sh.	b (Obs) %	b (Theo) %	w (Obs)	w (Theo)
Atenololc	13.8	65	66	3.4	3.4
Frusamide	9.8	56	56	2.8	2.8
GTN	9.2	57	54	2.6	2.7
Nifedipine	8.8	57	53	2.5	2.7
Captopril*	6.2	26	42*	3.8	2.3*
Propranolol	5.5	37	37	2.3	2.2
Bendroflu.	4.7	33	35	2.3	2.2
Cyclopenth.	3.9	22	30	2.8	2.1
ISMO	3.1	28	25	1.8	2.0
Digoxin	2.9	28	24	1.7	1.9
Spiro nol.	2.7	24	22	1.8	1.9
Bumetanide	2.4	21	21	1.9	1.9
ISDIN	2.3	20	20	1.8	1.9
Verapamilc	1.5	14	13	1.7	1.8
Average (excluding Captopril*)		36	35	2.3	2.3

For cardiovasculars, the averages at the foot of table 6.7 show the excellent overall fit of the Dirichlet. They also highlight the degree to which Captopril differs from the model predictions showing that one would expect this entity

to have more prescribers prescribing less frequently than is in fact the case. The table also shows that Cyclopentiazide is another entity which has a somewhat lower than expected penetration and consequently higher prescription frequency given its share of prescriptions.

The Dirichlet also recovers the observed Double Jeopardy pattern in cardiovascular prescribing very clearly. A large share entity such as Atenololc has five times the number of prescribers as Verapamilc, and the doctors who prescribe Atenololc do so on average twice as often as the smaller number of doctors who prescribe Verapamilc.

**Table 6.8 Penetration and Prescription Frequencies for Musculo-skeletals (month)**

4 weeks	Mkt Sh.	b (Obs) %	b (Theo) %	w (Obs)	w (Theo)
Ibuprofen	17.1	61	67	4.7	4.3
Naproxen	10.1	48	50	3.5	3.4
Coproxamolc	8.6	44	45	3.3	3.2
Paracodeine	7.2	39	40	3.1	3.0
Voltaren	6.3	37	36	2.9	2.9
Indomethacin	5.4	37	32	2.4	2.8
Piroxicam	5.3	32	32	2.8	2.8
Mefenamic	4.5	25	28	3.0	2.7
Ketoprofen	3.1	19	20	2.8	2.6
Average		38	39	3.2	3.1

In the case of musculo-skeletals, the Dirichlet predictions of penetration and prescription frequency are also very close to the observed data, again with a couple of minor exceptions. Ibuprofen appears to vary in a similar way to the cardiovascular entity Cyclopentiazide, whereas Indomethacin shows the opposite pattern with a lower prescription frequency than expected for its prescription share.

In both product fields the variations in penetration are greater than the frequencies and this pattern is recovered

by the Dirichlet. For cardiovasculars, penetrations vary by a factor of five in a quarter, and musculo-skeletal penetrations vary by a factor of four in a month. Prescription frequencies vary two-fold in a quarter for cardiovasculars and just over one and a half times for musculo-skeletal in a month. The Dirichlet successfully predicts the individual values for penetration and prescription frequency along with the Double Jeopardy pattern using only market shares as inputs into the model. The fit can be seen from the mean absolute deviations between the observed values and the model predictions. The cardiovascular penetrations have a M.A.D. of 2% and the prescription frequencies have a M.A.D. of 0.15. The corresponding figures for musculo-skeletal are 2.3% for penetration and 0.2 for prescription frequency.

#### **6.4 Growth in Penetration and Frequency**

The empirical patterns for the increase in the components of prescription growth through time were described for specific entities in **Section 4.3**. In the present section, the Dirichlet is used to model the growth of penetration and prescription frequency through time.

In table 6.9 the quarterly data for cardiovasculars is used to predict the annual figures and in table 6.10, the weekly data for musculo-skeletal is used to predict the data for a quarter. In both cases the actual figures are also shown.

Table 6.9 shows that the overall fit between the observed and theoretical values for cardiovascular prescribing is good with Captopril and Cyclopenthiazide again showing up as exceptions as noted in **Section 6.3**.

Table 6.10 shows a similar result for musculo-skeletal, with the Dirichlet providing good estimates for quarterly data from the monthly inputs. The largest discrepancy is found for Indomethacin, where the observed quarterly penetration is about 30% higher than predicted. Again this

entity was shown to be atypical in its Double Jeopardy pattern in Section 6.3.

**Table 6.9 Penetration and Prescription Frequencies for Cardiovasculars (quarter and year)**

	Quarter				Year			
	b (O) %	b (T) %	w (O)	w (T)	b (O) %	b (T) %	w (O)	w (T)
Atenololc	65	66	3.4	3.4	88	90	10.0	9.7
Frusamide	56	56	2.8	2.8	82	84	7.6	7.4
GTN	57	54	2.6	2.7	88	82	6.6	7.0
Nifedipine	57	53	2.5	2.7	85	82	6.6	6.9
Captopril*	26	42*	3.8	2.3*	47	72*	8.5	5.5*
Propranolol	37	37	2.3	2.2	66	68	5.2	5.1
Bendrofluazide	33	35	2.3	2.2	60	63	5.0	4.7
Cyclopentiazide	22	30	2.8	2.1	45	57	5.5	4.3
ISMO	28	25	1.8	2.0	54	50	3.8	4.0
Digoxin	28	24	1.7	1.9	57	48	3.2	3.9
Spironolactone	24	22	1.8	1.9	50	46	3.5	3.8
Bumetanide	21	21	1.9	1.9	42	42	3.7	3.7
ISDIN	20	20	1.8	1.9	44	41	3.4	3.6
Verapamilc	14	13	1.7	1.8	36	29	2.6	3.3
Average (excluding Captopril*)	36	35	2.3	2.3	61	60	5.1	5.2

**Table 6.10 Penetration and Prescription Frequencies for Musculo-skeletal (month and quarter)**

	Month				Quarter			
	b (O) %	b (T) %	w (O)	w (T)	b (O) %	b (T) %	w (O)	w (T)
Ibuprofen	61	67	4.7	4.3	79	84	10.9	10.3
Naproxen	48	50	3.5	3.4	67	69	7.6	7.4
Coproxamolc	44	45	3.3	3.2	63	63	6.9	6.9
Paracodeine	39	40	3.1	3.0	57	57	6.4	6.3
Voltaren	37	36	2.9	2.9	56	53	5.7	6.0
Indomethacin	37	32	2.4	2.8	62	48	4.4	5.7
Piroxicam	32	32	2.8	2.8	54	47	5.0	5.7
Mefenamic	25	28	3.0	2.7	40	42	5.7	4.4
Ketoprofen	19	20	2.8	2.6	31	32	5.0	5.0
Average	38	39	3.1	3.1	57	55	6.4	6.4

A measure of the predictive ability of the Dirichlet is given by the mean average deviation between the observed and the model values in the predicted time period. For cardiovascular prescription frequency in a year the M.A.D. is 0.4 and for musculo-skeletal it is 0.5.

The rates at which penetration and frequencies grow have important marketing implications. It is simple to use the observed penetrations and prescription frequencies for one period as inputs to gain Dirichlet predictions for time periods of different length. For example, even a small entity like Digoxin which has a market share of only 3% and is used by about 25% of doctors in 12 weeks is used by half of all doctors in a year. This finding is a direct output of the Dirichlet and shows that this is the normal state of affairs for an entity with such a share. Similarly, an entity such as Nifedipine with a 9% share is used by over 80% of all doctors in the course of a year.

The practical implication of these findings is discussed in **Section 6.10.**

#### **6.5 Prescribing the Product Class and Natural Monopoly**

A further empirical pattern from **Chapter 4** was the finding that the rate at which prescribers of each entity prescribed the product class showed little variation. However entities with large shares were prescribed by doctors who, on average, prescribed the product class slightly less frequently than did the prescribers of a small entity.

Tables 6.11 and 6.12 show the Dirichlet predictions for the aggregated entities in both product fields. For cardiovasculars (in a quarter) the Dirichlet predicts the product class prescribing rate well (M.A.D. = 1%) and although the observed product class prescription frequency (wp) figures show some slight variability, the Natural

Monopoly pattern is evident in both the observed and theoretical figures.

**Table 6.11 The Rate of Product Class Prescribing Cardiovasculars**

12 weeks	Market Share (%)	wp O	wp T
Atenololc	13.7	20	20
Frusamide	9.7	22	21
GTN	9.0	20	21
Nifedipine	8.8	21	21
Captopril	6.2	26	22
Propranolol	5.5	23	22
Bendrofluazide	4.7	24	23
Cyclopenthiazide	3.9	24	23
ISMO	3.1	23	23
Digoxin	2.9	26	23
Spiroinolactone	2.7	26	23
Bumetanide	2.4	25	23
ISDIN	2.3	23	24
Verapamilc	1.5	24	24
Average (excluding Captopril)	5.4	23	22

A similar pattern is observed with the musculo-skeletal product class in table 6.12, and again the Dirichlet models the observed pattern of Natural Monopoly with a mean average deviation of 1%.

**Table 6.12 The Rate of Product Class Prescribing Musculo-skeletal**

4 weeks	Market Share (%)	wp O	wp T
Ibuprofen	17.1	19	21
Naproxen	10.1	20	22
Coproxamolc	8.6	22	22
Paracodeine	7.2	22	22
Voltaren	6.3	20	22
Indomethacin	5.4	21	23
Piroxicam	5.3	20	23
Mefenamic	4.5	23	23
Ketoprofen	3.1	22	23
Average	7.5	21	22

### 6.6 Share of Requirements

In Chapter 4 it was found that large entities accounted for a higher proportion of their prescribers' needs than did small entities. This means that large entities attract higher degrees of loyalty than small entities.

This pattern is found to hold in tables 6.13 and 6.14 and the Dirichlet accurately predicts most of the individual entity share of requirements. The largest discrepancies are for the entities which have already been identified, but even in the case of Captopril the deviation is significant but not absolutely large. Thus, on average, Captopril accounts for 15% of its prescribers' needs in a quarter versus the 10% predicted by the Dirichlet.

**Table 6.13 Share of Requirements - Cardiovasculars**

12 weeks	O %	T %
Atenololc	17	16
Frusamide	13	13
GTN	13	12
Nifedipine	12	12
Captopril	15	10
Propranolol	10	10
Bendrofluazide	9	9
Cyclopentiazide	12	9
ISMO	8	8
Digoxin	7	8
Spironolactone	7	8
Bumetanide	8	8
ISDIN	8	8
Verapamilc	7	7
Average (excluding Captopril)	10	10

**Table 6.14 Share of Requirements - Musculo-skeletals**

4 weeks	O %	T %
Ibuprofen	24	21
Naproxen	18	16
Coproxamolc	15	15
Paracodeine	15	14
Voltaren	15	13
Indomethacin	12	13
Piroxicam	14	13
Mefenamic	14	12
Ketoprofen	13	11
Average	15	14

**6.7 Sole Prescribing**

Table 6.15 shows the penetration and prescription frequency of the sole prescribers for each of the entities along with

**Table 6.15 Sole Prescribing - Cardiovasculars**

4 weeks	bs O %	bs T %	ws O	ws T	w O
Atenololc	6.8	4.9	1.4	1.2	1.8
Frusamide	3.7	4.3	1.2	1.2	1.7
GTN	5.9	4.2	1.3	1.2	1.6
Nifedipine	6.0	4.1	1.2	1.2	1.5
Captopril	2.3	3.7	0.7	1.1	2.1
Propranolol	4.1	3.6	0.9	1.1	1.5
Bendrofluazide	2.8	3.5	1.1	1.1	1.5
Cyclopentiazide	3.3	3.4	0.6	1.1	1.8
ISMO	5.9	3.3	0.7	1.1	1.3
Digoxin	1.2	3.3	0.3	1.1	1.3
Spironolactone	2.1	3.3	0.4	1.1	1.3
Bumetanide	1.0	3.2	0.3	1.1	1.3
ISDIN	4.8	3.2	0.8	1.1	1.3
Verapamilc	2.9	3.1	0.4	1.1	1.3
Average (excluding Capoten)	3.9	3.6	0.8	1.1	1.5

**Note:** The observed frequency of sole prescribers for some entities is less than 1 because in some periods of 4 weeks that entity had no sole buyers at all.

the Dirichlet predictions. In addition the table shows the overall prescription frequency for all the doctors.

In a period as short as four weeks, only about 4% of doctors are loyal to one cardiovascular entity. Secondly, the Dirichlet predicts the proportion of sole prescribers very well. It recovers the prescription frequency of sole prescribers less effectively due to the artificially low averages (see note at the foot of table 6.15).

Recalculating the observed sole prescribing frequency for each entity to include only periods where sole prescribing occurred results in table 6.16.

**Table 6.16 Modified Sole Buying - Cardiovasculars**

4 weeks	ws O	ws T	w O
Atenololc	1.4	1.2	1.8
Frusamide	1.2	1.2	1.7
GTN	1.3	1.2	1.6
Nifedipine	1.2	1.2	1.5
Captopril	1.6	1.1	2.1
Propranolol	1.1	1.1	1.5
Bendrofluazide	1.1	1.1	1.5
Cyclopentiazide	1.1	1.1	1.8
ISMO	1.1	1.1	1.3
Digoxin	1.3	1.1	1.3
Spirolactone	1.0	1.1	1.3
Bumetanide	1.0	1.1	1.3
ISDIN	1.3	1.1	1.3
Verapamilc	1.1	1.1	1.3
Average (excluding Capoten)	1.1	1.1	1.5

Here the Dirichlet predictions are very close to those observed and a third point of note is that in no case does the prescribing frequency of sole prescribers exceed that of the population as a whole. In general, sole prescribers tend to prescribe at a lower rate than multi-entity prescribers.

The same pattern is to be found in the musculo-skeletal product field as shown in table 6.17.

**Table 6.17 Sole Buying - Musculo-skeletals**

1 week	bs O %	bs T %	ws O	ws T	w O
Ibuprofen	7.8	9.5	1.9	1.4	2.2
Naproxen	6.7	7.8	1.7	1.3	1.8
Coproxamolc	3.2	7.5	1.4	1.3	1.7
Paracodeine	3.5	7.2	1.3	1.3	1.7
Voltaren	7.9	7.0	1.5	1.3	1.6
Indomethacin	5.2	6.8	1.4	1.3	1.5
Piroxicam	6.0	6.8	2.1	1.3	1.7
Mefenamic	3.9	6.6	1.1	1.2	1.7
Ketoprofen	3.2	6.4	0.8	1.2	1.6
Average	5.3	7.3	1.5	1.3	1.7

In the case of the musculo-skeletal product field, it is necessary to reduce the analysis period to a week in order to find any significant incidence of sole prescribing. From these analyses, it is clear that sole prescribers are small in number and not attractive marketing targets.

While it might be argued that sole prescribing was a rather extreme measure of behaviour to analyse and model, it has been utilised many times before (eg Ehrenberg, 1988) and it is an easy measure to calculate. It is also interesting because it provides a rigorous test of the fit of the Dirichlet, and specifically how well it models the highly heterogeneous prescribing behaviour of doctors.

### 6.8 Duplication of Prescriptions

One of the key assumptions underlying the Dirichlet model is that the prescribing of one entity is independent of prescribing another. This means that the proportion of doctors prescribing both entity X and Y should be in proportion to the penetration of entity Y. This assumption is tested directly by examining the observed duplication



**Table 6.19 Duplication of Musculo-skeletal Prescriptions**

12 weeks Prescribers of:	Who also prescribe(%):								
	Ibr	Nap	Cop	Par	Vol	Ind	Pir	Mef	Ket
Ibuprofen		54	49	42	37	42	34	26	19
Naproxen	68		49	44	38	41	35	31	22
Coproxamolc	68	53		54	41	45	35	34	22
Paracodeine	66	55	62		37	41	35	35	22
Voltaren	61	49	49	39		40	35	28	20
Indomethacin	68	53	53	42	40		33	29	21
Piroxicam	65	52	49	43	41	39		30	21
Mefenamic	64	59	61	55	42	43	38		23
Ketoprofen	60	57	51	45	40	43	36	31	
Ave. Dup.	65	54	53	45	39	42	35	31	21
Pred.Dup.	69	54	50	44	42	42	36	28	21
Penetr.	61	48	44	39	37	37	32	25	19
Coef.	1.1								

For cardiovasculars, the mean average deviation of the observed average duplication from that predicted by the duplication law is 2.1% and the corresponding figure for musculo-skeletal is 1.7%. The duplication law is an empirical approximation to the duplications predicted by the Dirichlet, which tends to overestimate duplication rates for entities with high penetrations. For example, an entity with a penetration of 80% would have over 100% of duplicated prescribers if the duplication ratio was 1.3 and this can obviously not happen.

When the observed average duplications are compared to the Dirichlet average duplications, the M.A.D. for cardiovasculars (excluding Captopril) is 2.6% and for musculo-skeletal it is 3.0%. In both cases then, the models fit extremely well.

Table 6.20 shows how the observed duplication coefficients vary with the length of the analysis period for both product classes.

The pattern for the duplication coefficients is consistent with prior studies of varieties of the same product (Ehrenberg, 1988, p. 205), rather than between individual

brands. In this way, different drugs would be seen as complements rather than competitors.

**Table 6.20 Duplication Coefficients**

	1 wk	4 wks	12 wks	24 wks	48 wks
Cardiovasculars	1.9	1.5	1.3	1.2	1.1
Musculo-skeletal	1.3	1.1	1.1	1.1	1.0

### **6.9 Variation in Penetration and Prescription Frequency**

In Section 6.3 the Double Jeopardy pattern showed small but predicted differences in prescription frequencies across the two product classes and in Section 6.4 the growth of penetration and prescription frequency through time was modelled. Here the two elements are combined and the variation in penetration and prescription frequency across entities is examined.

In the case of cardiovasculars in a single week, the average prescription frequency is virtually constant at just over 1 and the difference between large and small entities lies almost exclusively in the penetration levels. In a year, this pattern changes somewhat with significant systematic variation in prescription frequency occurring. Table 6.21 shows that this variation is predicted by Dirichlet theory.

In the case of musculo-skeletal, the pattern is similar but more pronounced. In a week, the differences in prescription share show up almost exclusively in terms of penetration but in a year the variation is actually higher in frequency than penetration.

Looking at a specific cardiovascular entity, table 6.21 shows that Atenololc, which already has 15% of doctors prescribing in a week, has about six times as many prescribers in a year. Verapamilc, on the other hand, which has a penetration of only 2% in a week will see almost twenty times as many doctors prescribing in a year.

**Table 6.21 Penetrations and Prescription  
Frequencies for Cardiovasculars**

	1 WEEK		48 WEEKS			
	b O %	w O	b O %	b T %	w O	w T
Atenololc	14.7	1.2	87	90	10.0	9.7
Frusamide	10.8	1.2	82	84	7.6	7.4
GTN	10.8	1.1	88	82	6.6	7.0
Nifedipine	10.3	1.1	85	82	6.6	6.9
Captopril	6.3	1.3	47	72	8.5	5.5
Propranolol	6.3	1.1	66	68	5.2	5.1
Bendrofluazide	5.6	1.1	60	63	5.0	4.7
Cyclopenthazi	4.1	1.2	45	57	5.5	4.3
ISMO	3.8	1.1	54	50	3.8	4.0
Digoxin	3.6	1.1	57	48	3.2	3.9
Spirolactone	3.3	1.1	50	46	3.5	3.8
Bumetanide	3.0	1.1	42	42	3.7	3.7
ISDIN	2.9	1.1	44	41	3.4	3.6
Verapamilc	1.9	1.0	36	29	2.6	3.3
Average	6.2	1.1	60	61	5.4	5.2

**Table 6.22 Penetrations and Prescription  
Frequencies for Musculo-skeletal**

	1 WEEK		48 WEEKS			
	b O %	w O	b O %	b T %	w O	w T
Ibuprofen	33	2.2	93	95	37	36
Naproxen	23	1.8	87	85	23	24
Coproxamolc	21	1.7	81	81	22	22
Paracodeine	18	1.7	77	75	19	19
Voltaren	17	1.6	79	71	16	18
Indomethacin	15	1.5	86	65	13	17
Piroxicam	14	1.7	80	65	13	17
Mefenamic	11	1.7	62	59	15	15
Ketoprofen	8	1.6	55	46	11	14
Average	18	1.7	78	71	19	20

Atenololc's prescription frequency rises by about ten fold in a year, whereas Verapamilc's increases by just under three fold.

Table 6.22 shows that the leading musculo-skeletal, Ibuprofen has one third of doctors prescribing in a week, and will see its penetration rate rise by a factor of three and its prescription frequency by just under twenty in the course of a year.

In Chapter 4 it was pointed out that sales growth in a stationary market would have to come primarily from prescription frequency when penetration levels were already approaching 50%. Here this pattern is confirmed and the Dirichlet demonstrates its ability to show how with very frequently purchased goods, big brands will vary more in terms of frequency than penetration.

This is an important extension of knowledge about buyer behaviour in an fmcg type market. Prior studies (Ehrenberg, 1988) have shown that brands vary more in terms of their penetration rates than their purchase frequencies. The Dirichlet would predict, however, that in an extended time period (were the stationarity assumptions still to hold) brands would vary more in terms of their purchase frequency, and here is empirical confirmation of this theoretical prediction.

#### **6.10 A Practical Application of the Approach**

The practical implication of the variation in penetration and prescription frequency can be seen by considering hypothetical marketing objectives for Voltaren and Verapamilc. Assume objectives were set to increase sales of Voltaren by half to a 9% share and for Verapamilc to treble sales to a 4.5% share. As Voltaren already has 80% of doctors prescribing, the majority of the sales growth would have to come from existing prescribers prescribing more frequently. There would be some small increase in

penetration, but one would expect most of the growth to come from the prescription frequency rising from 16 to about 22 times in the year.

A marketing strategy designed to attract new users would be unlikely to succeed because the vast majority of doctors are already using the entity. On the other hand, Verapamilc is prescribed by just over one third of all doctors, whereas Bendrofluazide (an entity with a share close to the marketing target for Verapamilc) has a penetration rate of 60%. In this case, sales growth will come from more prescribers as well as increased frequency of prescription and so the marketing task is very different from the case of Voltaren.

### 6.11 Conclusions

The empirical patterns identified in **Chapter 4** were consistent with very different product markets studied previously. This consistency led to the successful application of the established Dirichlet model in this chapter. The theoretical assumptions which underlie the Dirichlet model (described in **Chapter 5**) generalise to this radically different product market.

The "Empirical then Theoretical then Empirical" approach (Ehrenberg, 1993) described in **Chapter 1** is used to extend knowledge of buyer behaviour patterns and confirm Dirichlet theory and its ability to predict differences between brands which are used by the vast majority of the population.

Overall, ethical pharmaceuticals differ little except in terms of their market shares. The empirically observed and Dirichlet patterns of prescribing are as expected with a few exceptions. The most significantly atypical entity, Captopril is the study of a separate analysis in **Chapter 9**.

The Dirichlet can be used as a management tool to help evaluate sales and marketing targets by gaining an understanding of the patterns of prescribing described here.

**PART III - NEW AND FAMILIAR PATTERNS**

**CHAPTER 7 - PRESCRIBING AT THE DIAGNOSIS LEVEL**

**CHAPTER 8 - PRESCRIBING OF BRANDS AND GENERICS**

**CHAPTER 9 - CAPOTEN- AN EXCEPTION TO THE RULE**

**CHAPTER 10 - PRESCRIBING ACROSS THE TWO PRODUCT CLASSES  
AND THE ROLE OF THE FAVOURITE BRAND**

## **CHAPTER 7: PRESCRIBING AT THE DIAGNOSIS LEVEL**

### **7.1 Introduction**

### **7.2 Product Differentiation with Respect to Diagnosis**

### **7.3 Diagnosis Prescribing Behaviour**

### **7.4 Market Partitioning**

### **7.5 Modelling the Product Fields as Aggregate Diagnoses**

### **7.6 Modelling Prescribing Behaviour at the Diagnosis Level**

### **7.7 Conclusions**

### **Appendices to Chapter 7**

### Summary

The previous chapter showed how the Dirichlet successfully models prescribing of Cardiovasculars and Musculo-skeletal. These two product classes can therefore be described in terms of random behavioural processes at the aggregate level. By analysing prescribing at the diagnosis level, this chapter demonstrates that there is indeed "method in the general practitioners' madness".

The Musculo-skeletal and Cardiovascular markets are both characterised by products which are differentiated with respect to diagnoses. Some drugs are widely prescribed for several diagnoses, but in the main most of a drug's prescriptions derive from one diagnosis and it is used far less in other diagnoses. Unlike previous studies the current research is able to provide an inter and intra-product class measure of differentiation. The cardiovascular product field demonstrates an average level of differentiation about twice that of the musculo-skeletal product field. On the other hand, the range of differentiation across drugs is similar in both product fields.

The effect of the different degrees of differentiation in both product fields is examined in **Section 7.6** in terms of prescribing behaviour measures. It shows that the resulting patterns are again consistent with Dirichlet theory

This chapter also extends the application of duplication analysis by examining duplications between prescribers of the same drug in different diagnoses. In a sense this is a 'three dimensional' approach which reveals a slight but detectable market partition. In a month, a doctor who prescribes a specific drug in one of the three musculo-skeletal diagnoses is, on average, 40% more likely to have prescribed it in another musculo-skeletal diagnosis than is a prescriber of any other drug. For cardiovasculars in a quarter, the corresponding figure is 20%.

This chapter also shows that the Dirichlet can be used to successfully model prescribing behaviour at the diagnosis level. Just as product classes can be modelled as the aggregate of the component brands, so can they be modelled here as the aggregate of their component diagnoses. The prescribing behaviour of doctors at the diagnosis level largely follows the Dirichlet norms. The measures of behaviour for an entity within a diagnosis is determined by its prescription share of that diagnosis, which tends to vary widely between diagnoses.

The main difference between the two product fields is that for musculo-skeletal a large share drug has a large share of two or three of the diagnoses. A small share drug has a small share in two or three diagnoses. For cardiovasculars the picture is different with large and small share drugs having large shares of just one diagnosis. What matters here is the dominance within the diagnosis and the size of the diagnosis. In this respect the pattern of cardiovascular diagnosis shares could be described as consistent with 'niche markets'.

### **7.1 Introduction**

**Section 7.2** analyses the prescription shares of the same entities in the different diagnoses in order to illustrate the systematic nature of pharmaceutical prescribing. It also reveals the pattern of competition in the product fields and also the degree to which entities are differentiated with respect to their diagnostic use.

**Section 7.3** examines entity penetrations and prescription frequencies by diagnosis, showing that there is considerable overlap between doctors prescribing the same drug in different situations. **Section 7.4** analyses the patterns of duplication between the same entity prescribed in different diagnoses in order to measure the extent of product market partitioning.

In Section 7.5 the Dirichlet is successfully used to model the diagnosis penetrations and prescription frequencies as components of the product class. This reproduces the 'Double Jeopardy' type pattern noted in Chapter 3 and provides a new application of the Dirichlet. Section 7.6 uses the Dirichlet to successfully model various measures of prescribing behaviour. Section 7.7 summarises the findings and proposes a simple classification scheme for comparing drugs using the dimensions of product differentiation and market partitioning.

In all the analyses in this chapter involving penetration levels, the absolute values (based on all 243 doctors in the panel) have been tabulated and used in model fitting.

### **7.2 Product Differentiation with Respect to Diagnosis.**

Manufacturers respond to evolving consumer requirements by developing new products which are differentiated from existing offerings. One example would be manufacturers such as Nestle and General Foods introducing de-caffeinated coffee in addition to the established caffeinated version. The extent to which differentiation occurred in the market place could only be measured if the consumers indicated a use to which the brand would be put at purchase. It would then be easy to measure the market shares for each usage situation. Ignoring the problem of coincidence of consumer intention and actual behaviour, it would be possible to characterise the degree of differentiation by computing the proportion of the brand's total sales accounted for by each use situation. These brand-use shares could then be compared with the share of the total category accounted for by each usage situation. If each brand-use share was similar to the corresponding usage situation's share of the total market, then the brand would be largely undifferentiated. If there were large differences then the brand would be differentiated. Such analyses would have to be both absolute and relative to understand the overall nature of differentiation in the product market. It could also reveal

the brands which are more (or less) differentiated and therefore one of the patterns of competition in the market.

Up to now, such an approach can only be pursued using attitudinal data, as no behavioural measures of brand and product use have been available with consumer panel data. In the current research however, the inclusion of the doctor's diagnosis allows direct observation of entity shares by usage.

In the pharmaceutical market, a product class market share could be comprised of equal shares across all diagnoses, or a large share of one diagnosis only, or some position in between these two extremes. The first situation would equate to a non-differentiated product offered to satisfy all diagnostic needs and the second to a differentiated product offered to satisfy just one need. The differentiated product could exist for two essential reasons in the case of prescribing. Either the active ingredients are only appropriate for one diagnosis or the regulatory authorities have only approved the drug's use for a specific purpose. This latter situation need not be static. As experience of a drug increases, the manufacturer could seek extensions of use to other diagnostic situations. One current example is the UK launch of Zantac in a reduced dose available without prescription from a chemist. This formulation will be marketed as a remedy for indigestion whereas in its prescription only guise, it is used in higher dosage in response to the diagnosis of gastric ulcers.

Tables 7.1 and 7.2 show the prescription shares of each entity within each diagnosis for the two product classes and the three musculo-skeletal and the five cardiovascular diagnoses. The total columns are identical to the entity shares within the product classes in tables 6.1 and 6.2.

**Table 7.1 Market Shares of Aggregated Entities: Cardiovasculars**

	Total %	D1 %	D2 %	D3 %	D4 %	D5 %
Atenololc	13	23	5	.	7	2
Frusemide	10	4	.	43	1	10
GTN	9	.	40	.	1	.
Nifedipine	9	9	18	.	.	4
Captopril	6	11	.	1	.	.
Propranolol	5	5	4	.	32	10
Bendrofluazide	5	7	.	4	.	2
Cyclopenthiazide	4	6	.	5	.	1
ISMO	3	0	13	.	.	.
Digoxin	3	0	0	7	30	5
Spirolactone	3	2	0	10	0	1
Bumetanide	2	1	.	12	.	3
ISDIN	2	0	10	.	.	.
Verapamilc	1	1	1	.	10	1
Other	24	31	7	16	18	59

Note: a 'dot' in table 7.1 indicates that the drug had an insignificant prescription share in that diagnosis.

**Table 7.2 Market Shares of Aggregated Entities: Musculo-skeletals**

	Total %	D1 %	D2 %	D3 %
Ibuprofen	17	18	16	8
Naproxen	10	10	10	10
Coproxamolc	9	11	5	3
Paracodeine	7	9	4	2
Voltaren	6	5	9	9
Indomethacin	5	4	7	11
Piroxicam	5	5	7	5
Mefenamic	5	6	2	1
Ketoprofen	3	2	6	6
All others	32	31	32	47

A few drugs are used widely for all diagnoses, but this is confined to the musculo-skeletal product class. The two clearest examples are Ibruprofen which has diagnosis share ranging from 8% to 18% and Naproxen which has a 10% share in all three diagnoses. Coproxamolc and Voltaren have significant shares in two of the three musculo-skeletal diagnoses. Paracodeine and Indomethacin have a significant share in just one diagnosis. The other musculo-skeletal entities all have a share of at least 5% in at least one diagnosis.

The cardiovascular entities tend to be used for one or at most two diagnoses to any significant degree, examples being Frusemide, Nifedipine and Propranolol. In general most cardiovasculars have large prescription shares of just one diagnosis, however they are also used for other diagnostic purposes where they attract much smaller prescription shares.

Tables 7.1 and 7.2 provide some indication of differentiation in these two product markets, but it is hard to evaluate the degree of differentiation or how it compares within product classes.

In order to emphasise the difference between the two product classes, the biggest three entities for each of the cardiovascular diagnoses are shown in table 7.1a and the diagnosis share which they account for is shown at the foot of the table.

This shows that in general the large share drugs in each diagnosis are different, whereas in table 7.2, drugs with large shares of one musculo-skeletal diagnosis frequently have large shares of other diagnoses as well.

In this sense then the cardiovascular product field exhibits far greater differentiation with respect to diagnosis than does the musculo-skeletal product class.

**Table 7.1a Market Shares of Aggregated Entities: Selected Cardiovasculars**

	D1 %	D2 %	D3 %	D4 %	D5 %
Atenololc	23				
Captopril	11				
Other	31				
GTN		40			
Nifedipine		18			
ISMO		13			
Frusemide			43		
Bumetanide			12		
Spirolact.			10		
Propranolol				32	
Digoxin				30	
Verapamilc				10	
Frusemide					10
Propranolol					10
Other					59
Top Three	65	71	65	79	72

In order to check that the diagnosis shares of each product field were significantly different, chi square tests were run on the raw data from which tables 7.1 and 7.2 were generated. Because the prescriptions in each diagnosis are largely written by the same doctors, the data is not strictly independent and the application of a chi square test relies on independent samples. The analysis should therefore perhaps be termed an 'approximate chi square test', but given the size of the statistics, there is no doubt that the diagnosis shares are different.

**Table 7.3 'Approximate Chi Square' Statistics for Prescribing at the Diagnosis Level**

	Chi Square	DF
Musculo-skeletal	2700	18
Cardiovasculars	21000	56

As a further test, the prescription shares of the aggregated entities were calculated in each diagnosis for six different demographic sub-groups: British, Other Ethnic origin, Male, Female, Young and Old. These shares were then compared to the overall diagnosis shares in tables 7.1 and 7.2 and mean absolute deviations were computed across diagnoses and entities. The resulting MADs for both product fields were about 1%. This analysis then, uses six further samples which give very similar market share patterns, and this effectively shows that the diagnosis patterns are consistently different. It also shows that demographic differences are not the cause of the variability in prescription share of the diagnoses.

Having demonstrated that diagnosis shares were different from product class shares, the next step was to calculate a measure of differentiation for each entity with respect to the diagnoses in each product class. The detailed procedure is shown for musculo-skeletals and derived from the data in table 7.2.

**Table 7.4 Differentiation Within Musculo-skeletals**

	Diagnosis Share of Prescriptions			Deviation from Total			MAD
	D1	D2	D3	D1	D2	D3	
Ibuprofen %	69	29	2	+4	-1	-2	2
Naproxen %	64	31	4	-2	+1	0	1
Coproxamolc %	80	18	1	+14	-13	-3	10
Paracodeine %	81	19	1	+15	-11	-3	10
Voltaren %	49	44	6	-17	+14	+2	11
Indomethacin %	53	40	8	-12	+9	+4	9
Piroxicam %	57	39	4	-9	+9	+1	6
Mefenamic %	84	16	0	+19	-15	-4	13
Ketoprofen %	35	58	8	-31	+27	+4	20
Tot. Category %	65	30	4	MAD 14	11	2	
				Avg			9

Table 7.4 should be read as follows: Diagnosis 1 accounts for 69% of all Ibuprofen prescriptions and it accounts for 65% of all musculo-skeletal prescriptions. This means that

the deviation from the overall share is 4% for Ibuprofen. The deviations for each brand and each diagnosis are then averaged to give the MAD in the last column of table 7.4.

Table 7.5 presents the mean deviation for each brand in decreasing order. Ketoprofen is the most differentiated musculo-skeletal and Naproxen the least differentiated. The average figure at the foot of the table gives a benchmark for evaluating the degree of differentiation compared to the other product class.

**Table 7.5 Musculo-skeletal Differentiation Coefficients**

Entity	MAD %
Ketoprofen	20
Mefenamic	13
Voltaren	11
Coproxamolc	10
Paracodeine	10
Indomethacin	9
Piroxicam	6
Ibuprofen	2
Naproxen	1
Average	9

Table 7A.1 in the appendix presents the same data for cardiovasculars and shows that the overall level of differentiation as measured by the table average of 20% is larger than for musculo-skeletal, but that the range from 10-30% is similar to that for musculo-skeletal.

The deviation figures in table 7.4 do appear to show patterns which are consistent for some drugs. Ibuprofen and Naproxen show a quite similar pattern of share deviations. Mefenamic, Paracodeine and Coproxamol share a pattern as do Indomethacin and Voltaren. If doctors see drugs as sufficiently similar or complementary, then such patterns would be expected.

The cardiovascular data illustrate an interesting point in that GTN is the most differentiated entity with respect to diagnosis and Nifedipine the least differentiated. Nevertheless, these two entities are the main drugs used in diagnosis 2. Similar, but less marked, examples are found in the musculo-skeletal product class and one conclusion is that the patterns of competition are not necessarily reflected in patterns of differentiation. Another conclusion is that differentiation does not necessarily convey a market share advantage. In the musculo-skeletal product field, the largest share drugs are those which are less differentiated.

By and large, product differentiation is the norm to a greater or lesser extent, with Naproxen, Ibuprofen and Piroxicam examples of non-differentiated product offerings.

More research is required to see whether these findings generalise further.

### 7.3 Diagnosis Prescribing Behaviour.

When analysing the diagnosis shares in Section 7.2 it was noted that Naproxen has a 10% share in all three musculo-skeletal diagnoses but it is not clear whether it is the same or different doctors who use the drug in the different situations. This section looks at drug penetrations and prescription frequencies by diagnosis to see if these measures reveal diagnostic overlap. The analysis in the following section completes the empirical picture by examining the duplications between prescribers of the same drug in different diagnoses. Sections 7.5 and 7.6 then use the Dirichlet to model these and another measure of prescribing behaviour.

Tables 7.6 and 7.7 tabulate the penetrations and prescription frequencies for the entities in the two product classes.

Naproxen (Napr) with a 10% share in all diagnoses (see table 7.2) is prescribed by about half of the doctors for diagnoses 1 and 2 and by just 15% of doctors for diagnosis 3. As the penetration of Naproxen for the total product field is 70%, this means that it is not the same doctors prescribing in all three situations, but there is a great deal of overlap with most doctors who prescribe the drug doing so for the two large diagnoses. The fact that 'only' 15% of doctors prescribe Naproxen for diagnosis 3 is consistent with the average rates at the foot of table 7.7. Naproxen is the second or third biggest entity in all diagnoses, and in all cases it has a higher than average penetration level.

**Table 7.6 Penetrations and Prescription Frequencies by Diagnosis (Cardiovasculars, 48 weeks)**

	Total		D1		D2		D3		D4		D5	
	b	w	b	w	b	w	b	w	b	w	b	w
Ate	87	10.0	83	9.3	35	2.1	.	.	12	1.8	5	1.3
Fru	82	7.6	40	3.7			73	6.0	.	.	15	2.0
GTN	88	6.6	.	.	88	6.5						
Nif	85	6.6	69	4.2	65	4.0	.	.	2	1.4	.	.
Cap	47	8.5	44	8.7	.	.	.	.	.	.	.	.
Pro	66	5.2	43	3.7	24	2.1	.	.	35	2.9	15	2.0
Ben	60	5.0	54	4.6	.	.	20	2.2	.	.	.	.
Cyc	45	5.5	37	5.3	.	.	21	2.2	.	.	.	.
ISM	54	3.8	-	-	53	3.6	.	.	.	.	.	.
Dig	57	3.2	-	-	-	-	34	2.2	36	2.7	7	1.9
Spi	50	3.5	20	3.2	-	-	40	2.6	.	.	-	-
Bum	42	3.7	.	.	.	.	33	3.6	.	.	7	1.3
ISD	44	3.4	-	-	42	3.3	.	.	.	.	.	.
Ver	36	2.6	.	.	11	1.8	.	.	16	1.9	.	.
avg	60	5.4	49	5.3	45	3.3	37	3.1	20	2.1	10	1.7

**Note:** a 'dot' in table 7.6 indicates that the drug had an insignificant prescription share in that diagnosis. A 'dash' indicates that the drug was not prescribed for that diagnosis.

**Table 7.7 Penetrations and Prescription Frequencies by Diagnosis (Musculo-skeletal, 12 weeks)**

	Total		D1		D2		D3	
	b	w	b	w	b	w	b	w
Ibup	79	10.9	66	9.1	63	4.0	12	1.3
Napr	67	7.6	53	6.1	48	3.3	15	1.4
Copr	63	6.9	57	6.1	33	2.3	5	1.2
Para	57	6.4	50	5.8	29	2.4	3	1.1
Volt	56	5.7	37	4.3	44	3.2	12	1.5
Indo	62	4.4	43	3.3	39	2.8	16	1.4
Piro	54	5.0	36	4.3	38	2.8	8	1.2
Mefe	40	5.7	36	5.3	16	2.3	1	1.2
Keto	31	5.0	16	3.5	26	3.5	8	1.6
Aver	57	6.4	44	5.3	37	3.0	10	1.3

In this case then, it appears that the penetration levels (and hence prescription frequencies) are primarily driven by the shares within the diagnostic categories.

Indomethacin has an 11% share in diagnosis 3 and is prescribed by 16% of doctors. This is the highest penetration in this diagnosis. In diagnosis 1 where Indomethacin has only a 4% share it is prescribed by as many as 43% of doctors.

In general, Tables 7.6 and 7.7 show that an entities' penetration and prescription frequency in a particular diagnosis is largely determined by its share of diagnosis prescriptions. The main exception to the pattern is again Capoten (Cap) which is discussed in detail in Chapter 9.

While the majority of drugs are mainly prescribed for one diagnosis there are no 'niche' entities in the two product fields, the penetration and prescription frequencies in one diagnosis generally appear to be independent of those in other diagnoses. This independence is explored through duplication analysis in the following section.

#### 7.4 Market Partitioning

Like Product Differentiation, there are two potential extremes which characterise the degree of market partitioning. A highly partitioned market would be described by high (or low) duplications between the same entity in different diagnoses when compared to the average for all the entities. This would result in a segment of doctors who were more (or less) likely to prescribe a specific entity in one diagnosis if they already prescribed it for another diagnosis. The non-partitioned situation would be described by a pattern where individual duplications were in line with entity penetrations. By examining the duplication pattern the size of any partitioning effect can be revealed.

For example, as noted in table 7.2, Naproxen has a 10% share in each diagnosis. This could reflect the same doctors (as far as possible) prescribing the entity for all three diagnoses and resulting in high duplications. The opposite result could arise from largely different doctors prescribing the brand for each diagnosis giving rise to low duplications. The alternative would be no special duplication tendencies so that duplications were in line with entity penetrations in the specific diagnosis. Similarly, Indomethacin has twice the share in musculo-skeletal diagnosis 3 compared to diagnosis 1. This could arise from the same doctors prescribing for both diagnoses but with differing frequencies of prescription.

In general, is it all the same doctors prescribing the same entities in different diagnoses or at the other extreme is it all different doctors with doctors only prescribing an entity for one diagnosis? The first extreme would be represented by duplications of 100% and the latter by duplications of 0%.

The tabulations in the previous section already provide some indication as to the actual degree of partitioning within the range between these extremes.

Table 7.8 shows the duplications for five musculo-skeletals in the three different diagnoses. Duplications between the same drug in different diagnoses are highlighted in bold.

The table should be read as follows: of the doctors who prescribed Ibuprofen (Ibup) for diagnosis 1, 55% also prescribed it for diagnosis 2, 7% for diagnosis 3 and so on.

Table 7.8 Duplication of Prescribing between the Same Entity in Different Diagnoses - Musculo-skeletals

Weeks Prescribers	% who also prescribe														
	Ib1	Ib2	Ib3	Na1	Na2	Na3	Co1	Co2	Co3	In1	In2	In3	Me1	Me2	Me3
Ibup 1	-	<b>55</b>	<b>7</b>	42	32	6	42	19	2	28	22	7	23	7	0
Ibup 2	<b>67</b>	-	<b>8</b>	39	34	7	45	23	2	26	25	7	25	9	1
Ibup 3	<b>69</b>	<b>62</b>	-	40	25	7	55	20	6	29	34	14	23	8	0
Na 1	56	43	5	-	<b>49</b>	<b>9</b>	40	18	2	27	21	7	27	8	1
Na 2	53	46	4	<b>62</b>	-	<b>11</b>	40	22	3	26	23	7	29	10	1
Na 3	51	47	6	<b>52</b>	<b>53</b>	-	38	23	3	25	23	11	30	13	1
Co 1	52	46	7	37	29	6	-	<b>30</b>	<b>3</b>	30	23	8	32	10	1
Co 2	52	52	6	37	36	8	<b>67</b>	-	<b>5</b>	26	26	9	30	12	1
Co 3	48	41	15	46	39	9	<b>67</b>	<b>48</b>	-	43	39	28	28	20	2
In 1	56	43	6	40	31	6	48	19	3	-	<b>40</b>	<b>10</b>	27	10	0
In 2	53	48	8	37	32	7	44	22	4	<b>47</b>	-	<b>12</b>	27	11	0
In 3	52	41	11	37	31	11	48	23	8	<b>37</b>	<b>37</b>	-	23	8	2
Me 1	48	44	5	43	37	8	55	23	2	28	25	7	-	<b>23</b>	<b>2</b>
Me 2	40	46	5	35	37	10	50	27	5	31	30	7	<b>66</b>	-	<b>4</b>
Me 3	21	38	0	27	27	11	48	27	5	16	5	16	<b>54</b>	<b>48</b>	-
Ave (S)	<b>68</b>	<b>59</b>	<b>7</b>	<b>57</b>	<b>51</b>	<b>10</b>	<b>67</b>	<b>39</b>	<b>4</b>	<b>42</b>	<b>38</b>	<b>11</b>	<b>60</b>	<b>36</b>	<b>3</b>
Ave (O)	52	45	7	38	32	8	46	22	4	28	25	11	27	11	1
Net.	47	39	5	35	28	6	38	17	2	24	20	6	22	8	1
Coef S	<b>1.8</b>														
Coef O	1.2														

There are two averages towards the foot of the table: Ave (S) is the average duplication between the same drug in different diagnoses and Ave (O) is the average duplication between one drug in a specific diagnosis and all the other drugs in any diagnosis. The table confirms that neither of the two extremes proposed above occur in practice, but in

all cases the average duplication between the same drug in different diagnoses is the greater of the two.

Table 7.8 shows that there are higher than average duplications between the same entities in different diagnostic situations. For example one would expect that about 11% of prescribers of any entity in any diagnosis would also prescribe Mefenamic for diagnosis 2. It is observed however, that about 50% of the doctors who prescribe Mefenamic for diagnosis 3 also prescribe it for diagnosis 2.

The duplication coefficients at the foot of the table summarise the incidence of higher than expected duplications and are derived by taking the mean of the average duplications and dividing by the mean of the entity penetrations. The corresponding figures for cardiovasculars in a quarter are also shown in table 7.8a.

**Table 7.8a Duplication Coefficients for Prescribing the Different Diagnoses (month and quarter)**

	Musculo- skeletal 4 weeks	Cardio- -vasculars 12 weeks
Same entities Different diagnoses	1.8	1.5
All entities Different diagnoses	1.2	1.3

Table 7A.2 in the chapter appendix shows the same analysis for a range of cardiovascular entities in different diagnoses.

On average, for the same entities in different diagnoses, the duplications are 80% higher than expected for musculo-skeletal in a month and about 40% greater for cardiovasculars in a quarter.

The time periods chosen for the analysis are important for two reasons. Firstly, they demonstrate the short term market partitioning effects inherent in pharmaceutical prescribing. Secondly, Dirichlet theory would predict that as the length of the analysis period increases the duplication coefficients should decrease. Duplication tables covering a quarter for musculo-skeletal and a year for cardiovasculars are to be found in the chapter appendix (tables 7A.3 and 7A.4) but the relevant effect is summarised in table 7.9 and shows that the duplication coefficients do indeed decline through time, and that there is still a weak market partition observable.

**Table 7.9 Duplication Coefficients for Prescribing the Different Diagnoses (quarter and year)**

	Musculo- skeletal 12 weeks	Cardio- -vasculars 48 weeks
Same entities Different diagnoses	1.4	1.3
All entities Different diagnoses	1.1	1.2

For musculo-skeletal in 12 weeks, duplications are an average of 40% higher than predicted and for cardiovasculars in a year the corresponding figure is 20%. Here then is evidence that there remains some degree of partitioning but that the level declines as the length of the analysis period increases.

This analysis shows therefore, that some segmentation does exist but that it is of a minor form, similar to that described in Section 4.9 when different strengths of the same drug were compared.

In the case of cardiovasculars, there are some higher than expected duplications which persist, but in a year the duplication coefficients are virtually the same summarising the general lack of partitioning in this time period.

The summary data in table 7.9 mask some specific deviations from the sub-pattern. In the case of musculo-skeletal for example, Mefenamic has relatively high duplications between diagnoses given the diagnosis penetration levels, and Coxproxamolc is an entity with very much higher than expected duplications which persist over a quarter as shown in the appendix to the chapter.

In addition, the average summary data reflect the fact that there are some cardiovascular entities which do not have higher than expected duplications between the different diagnoses. This contrasts with musculo-skeletal where all entities have high intra-diagnostic duplications.

It is important to stress that this research is the first time that it has been possible to fit the Dirichlet to any kind of disaggregated data based on usage situation. If the patterns are found to hold, as explored in Sections 7.5 and 7.6 below, then this provides new knowledge about the range of situations in which it can be applied.

### 7.5 Modelling the Product Fields as Aggregate Diagnoses

In Chapter 3 a pattern similar to Double Jeopardy was noted when comparing the prescribing behaviour within the diagnostic sub-classes of the product fields. It was pointed out that the formal Double Jeopardy pattern applies only to brands which are highly substitutable or complementary by virtue of their similarity. One parallel would be store choice, with diagnoses equating to store chains. Buyer behaviour has been analysed within and across store chains (see for example Uncles and Ellis, 1989). Dirichlet theory permits the aggregation of brands into 'super brands' and an individual store chain is analogous to a brand. Store chain data can be aggregated to provide a picture of the whole market and reveal double jeopardy patterns reflecting the differing market shares of retailers. Given the intrinsic

similarity between retailers, these findings are unsurprising.

In the case of the current research however, the diagnoses represent very different situations which are not directly comparable. It is clearly inappropriate to categorise osteoarthritis as very similar to a slight muscle strain. Similarly, hypertension is significantly different to heart failure and these differences lead to the different prescribing patterns described in table 3.10.

Because of these differences, it cannot be assumed that the Dirichlet would successfully model prescribing behaviour at the diagnosis level. On the other hand, a product class is comprised of the aggregate diagnoses, despite the obvious contrast between diagnoses. One obvious experiment was to use the raw data (summarised by table 3.10) as the inputs into the Dirichlet.

Table 7.10 shows the fit for diagnosis penetration and prescription frequencies for cardiovasculars and table 7.11 shows the same data for musculo-skeletals.

To help interpretation,  $B_D$  is defined as the proportion of doctors who prescribe at least once for a diagnosis in a specified time period and is defined as the diagnosis penetration.  $W_D$  is the number of prescriptions written for the diagnosis divided by the number of prescribing doctors.

The Dirichlet here, therefore, is fitted to the share of the product class accounted for by each diagnosis.

For cardiovascular diagnoses, the Dirichlet models penetration and prescription frequency well, as can be seen by the averages at the foot of table 7.10. As a result the Dirichlet reproduces the 'Double Jeopardy' type pattern of the observed data.

**Table 7.10 Penetration and Prescription Frequencies  
for Cardiovasculars**

Diagnosis	Month				Quarter			
	B <sub>D</sub> (O)	B <sub>D</sub> (T)	W <sub>D</sub> (O)	W <sub>D</sub> (T)	B <sub>D</sub> (O)	B <sub>D</sub> (T)	W <sub>D</sub> (O)	W <sub>D</sub> (T)
Hypertension	71	73	3.9	3.8	89	89	9.5	9.4
Angina	53	50	2.3	2.4	78	74	4.6	4.8
Heart Failure	38	41	2.2	2.1	62	64	4.1	3.9
Arrhythmia	19	17	1.4	1.6	38	31	2.1	2.5
Other	15	15	1.5	1.6	33	29	2.2	2.5
Average	40	39	2.3	2.3	60	58	4.5	4.6

**Table 7.11 Penetration and Prescription Frequencies  
for Musculo-skeletals**

Diagnosis	Week				Quarter			
	B <sub>D</sub> (O)	B <sub>D</sub> (T)	W <sub>D</sub> (O)	W <sub>D</sub> (T)	B <sub>D</sub> (O)	B <sub>D</sub> (T)	W <sub>D</sub> (O)	W <sub>D</sub> (T)
Miscellaneous	72	72	3.8	3.8	99	96	33.5	34.2
Rheum. Arthritis	56	55	2.3	2.3	98	93	15.7	16.6
Osteo-Arthritis	13	14	1.3	1.3	64	60	3.3	3.5
Average	47	47	2.5	2.5	87	83	17.5	18.1

In the case of musculo-skeletals, the fit of the model for a week is also excellent, but it is not quite as good for the quarterly predictions. Here the Dirichlet seems to under predict penetration rates and over predict prescription frequencies. The reason for these discrepancies is not clear, but may relate to the observed penetration levels for diagnoses 1 and 2 which are close to 100%.

Overall, the Dirichlet is able to predict prescribing at the diagnosis level in the short term very well and this provides a new application of the model. Given the very different nature of the diagnoses, the fit with Dirichlet theory is remarkable.

The finding arose by testing the empirically observed pattern against the established model (E then T) and also

using the established theory and applying it to the new situation (T then E).

#### **7.6 Modelling Prescribing Behaviour at the Diagnosis Level**

In the previous section it was shown that the Dirichlet can be used to model the product class as the aggregate of its individual diagnoses. The question remains, however, as to whether the Dirichlet will successfully model individual drug prescribing at the diagnosis level given the intra-diagnosis partitions noted in Section 7.3. In this section, then, the Dirichlet is used to model aspects of prescribing behaviour for the same drugs in different diagnostic situations.

If the Dirichlet is found to hold, then it could be argued that the level of analysis still obscures the real patterns of loyalty and segmentation. For example, the diagnostic classifications in the Jigsaw database could be too broad to reveal doctor preferences for specific drugs in specific circumstances.

Alternatively, the level of aggregation used for this analysis could be too broad to reveal underlying loyalty to specific brands or forms of a drug. This latter problem will be addressed in Chapter 8, but the former potential problem is one that cannot be resolved in the context of this research, and in any case is unlikely to represent reality. If a chemical was developed to solve a specific diagnostic situation and it was successful and profitable, then competitive forces would result in other firms developing similar products. The existence of patents in the pharmaceutical industry does not prevent such development. Returning to the example of drugs to control ulcers, the first patented chemical was Cimetidine marketed as Tagamet. This drug was so successful that it encouraged the existing R&D programme at Glaxo who developed a different patentable chemical called Rantidine which was marketed as Zantac in direct competition to Tagamet.

In order to model at the diagnosis level, the raw data relating to each of the eight diagnoses were separately analysed using the BUYER package, and so the Dirichlet was fitted to the diagnosis share of individual drugs in each diagnosis where it was prescribed.

The data for the selected entities and diagnoses were then extracted and reconstituted in table 7.12 which shows selected observed and predicted values for various measures of cardiovascular prescribing behaviour.

The entities for these tables were chosen from table 7.1 in order to examine the fit of the Dirichlet for the same entities having contrasting prescription shares in the different diagnoses (the observed penetrations and prescription frequencies are also found in table 7.7). A similar analysis for musculo-skeletal was conducted and the results are found in table 7A.5 in the appendix.

Table 7.12 shows that in general the Dirichlet provides an excellent fit to the observed measures of prescribing behaviour in the different diagnoses and therefore that it is diagnosis share which largely determines the reality of prescribing behaviour. For example, table 7.2 shows the share for Atenololc as 23% for diagnosis 1, 5% for diagnosis 2 and 2% for diagnosis 4 and table 7.12 shows that these market shares equate to very different numbers of prescribers and average frequency of prescription, but in a way which is predicted by the Dirichlet.

Two of the three largest deviations from the model involve penetration and prescription frequencies (Nifedipine in diagnosis 1, and Bumetanide in diagnosis 3) and the third is the poor fit in predicting the rate at which prescribers of Spironolactone in diagnosis 1 prescribe in total for diagnosis 1. Even in these cases, the other prescribing behaviour measures are still modelled well and the

predictions for the same entities in other diagnoses are also close to those observed.

**Table 7.12 Observed and Predicted Prescribing Behaviour, Cardiovascular Diagnoses.**

48 weeks	b <sub>o</sub> b <sub>t</sub>	w <sub>o</sub> w <sub>t</sub>	wp <sub>o</sub> wp <sub>t</sub>	D <sub>o</sub> D <sub>p</sub>
<u>Atenololc</u>				
Diag 1	83 86	9.3 9.0	38 38	91 95
Diag 2	35 38	2.1 2.0	20 21	33 30
Diag 4	5 4	1.3 1.8	7 7	5 7
<u>Frusamide</u>				
Diag 3	73 73	6.0 6.0	13 14	93 99
Diag 1	40 38	3.7 3.8	49 45	47 45
<u>Nifedipine</u>				
Diag 1	69 59*	4.2 4.9*	42 43	78 78
Diag 2	65 72	4.0 3.6	18 18	63 62
<u>Propranolol</u>				
Diag 5	35 43	2.9 2.4	6 6	54 55
Diag 2	24 29	2.1 1.8	20 22	22 21
<u>Digoxin</u>				
Diag 5	39 42	2.7 2.3	6 6	49 56
Diag 4	7 7	1.9 1.8	7 7	9 12
<u>Spiroolac.</u>				
Diag 3	40 44	2.6 2.4	16 18	54 55
Diag 1	20 20	3.2 3.3	62 47*	26 23
<u>Bumetanide</u>				
Diag 3	33 46*	3.6 2.5*	18 18	48 44
Diag 4	7 5	1.3 1.8	8 7	12 10
<u>Verapamilc</u>				
Diag 5	16 20	1.9 1.6	7 8	30 25
Diag 2	11 12	1.8 1.5	22 23	9 8
mean	33 35	3.1 3.0	19 19	43 43
MAD	2.9	0.3	0.9	2.7

**Note:** MAD computed excluding entries marked with \*  
 o = Observed, t = Dirichlet Prediction,  
 p = Predicted from Duplication Coefficient.

In the case of Nifedipine in diagnosis 1 it seems that the deviation is due to a surplus of light prescribers and for Bumetanide in diagnosis 3 the higher than expected

prescription frequency is caused by just one doctor prescribing the entity 22 times in a year, which is an unexpectedly high frequency for its prescription share.

As a summary of the fit of the model, column averages are computed along with the mean absolute deviations and are shown at the foot of table 7.13. Correlation analysis was also conducted and revealed r-square values of over 0.98 for all the prescribing behaviour measures in both the cardiovascular product field here and also musculo-skeletal as shown in the appendix (see table 7A.5).

For completeness, tables 7A.6 - 7A.13 in the appendix show the fit of the Dirichlet with the main entities for each diagnosis in decreasing prescription share order.

These tables give a further eight illustrations of the Double Jeopardy effect, and show the success of the Dirichlet in modelling penetrations and prescription frequencies. They also confirm that these two key measures of prescribing behaviour are largely determined by the individual entity's prescription share of the diagnosis.

The fit of the Dirichlet at the diagnosis level underlines the small size of the partitioning effect noted in **Section 7.4**. Any major partitioning by diagnosis would have been reflected in a poorer fit.

### **7.7 Conclusions**

This chapter has provided an insight into the way in which different uses for the same item can be successfully modelled using the Dirichlet. In the case of the current research it can be used to model product class prescribing behaviour by aggregating the diagnoses and also model entity prescribing within each diagnosis.

The existence of different diagnoses provides the opportunity to describe the degree of product

differentiation with respect to usage. While the number and size of diagnoses obviously affects the degree of potential differentiation there are differences between the two product classes studied. These differences are consistent with the concept of differentiation giving rise to distinct sub-markets or niches. The effect is not absolute, and the hypothesis that any such measure would be very much weaker in consumer goods markets seems reasonable given the importance of, say, heart disease when compared to detergents.

Weak segmentation exists in this market with prescribers of an entity in one diagnosis more likely to prescribe it for another diagnosis than the average doctor. The partitioning is not exclusive and decreases through time, but the pattern together with the general fit of the Dirichlet across diagnoses does suggest a possible application for understanding and planning brand extensions versus new brand launches.

The market partitions observed in **Section 7.4** are consistent with the patterns of differentiation seen in **Section 7.2**. The cardiovascular product field showed higher average levels of differentiation than musculo-skeletal, from which lower partitioning would be expected.

Given the variability between drugs and product classes that exists in terms of differentiation and partitioning it is possible to develop a basis for classifying individual drugs accordingly. A simple model is shown in figure 7.1.

**Figure 7.1 Characterising Segmentation and Differentiation**

	<u>Differentiation</u>		
	<u>Yes:</u> Different Diagnosis Shares		<u>No:</u> Equal Diagnosis Shares
<u>Partit-</u>	<u>Yes:</u> High Duplications	Specialised segment	General segment
<u>ioning</u>	<u>No:</u> Unit Duplications	Specialised	General

This framework can also be used to comparatively characterise the two product classes. Musculo-skeletal with less differentiation and more partitioning than cardiovasculars would tend to the top right quadrant whereas cardiovasculars with more overall differentiation but less partitioning would tend towards the bottom left quadrant. In practical marketing terms these differences might be reflected in the ways that pharmaceutical companies organised their product development, promotional efforts and detailing resource.

Within product classes the model might be used to help understand how drugs compete. Once the pattern of market shares has been revealed, one can then identify the diagnostic entities which might be considered as 'competitors' by looking at tables 7.1 and 7.2 to see the entities which have large shares in each diagnosis situation. Next, the degree of differentiation can be revealed by referring to table 7.5 and to table 7A.1 in the appendix to this chapter.

The overall level of differentiation will be largely determined by the number of diagnoses and the nature of the product class, but as shown in Section 7.2 there is likely

to be some variability between drugs which determines how general is their use and therefore how they could be marketed. The extent and persistence of any partitioning between the prescription of the same drug in different diagnoses could have implications for the type of marketing programme appropriate for different product classes and different drugs within the product class. An understanding of the relative positions along the two dimensions of the drugs in a product class could provide the basis for modifying sales targets or setting goals for new brand launches.

Figure 7.2 classifies some of the entities into the differentiation/partitioning matrix but it should be noted that most entities are located in the bottom left hand quadrant.

**Figure 7.2 Characterising the Entities**

	Differentiation	
	Yes	No
Yes	Mefenamic	Naproxen
<b>Partit- ioning</b>	Digoxin	Propranolol
No	Ketoprofen	Ibuprofen
	Frusamide	Atenololc

Appendix to Chapter 7**Table 7A.1 Cardiovascular Differentiation Coefficients**

Entity	MAD %
GTN	31
Digoxin	30
ISDIN	30
ISMO	30
Bumetanide	28
Frusamide	22
Verapamilc	20
Captopril	18
Spironolactone	18
Atenololc	14
Bendrofluazide	13
Cyclopenthiazide	12
Propranolol	12
Nifedipine	10
Average	21

This table shows the degree of differentiation with respect to the five cardiovascular diagnoses. The average level compares to 9% for musculo-skeletals, but the range is similar.

**Table 7A.2 Observed and Predicted Prescribing Behaviour, Musculo-skeletals.**

	b <sub>o</sub> b <sub>t</sub>	w <sub>o</sub> w <sub>t</sub>	wp <sub>o</sub> wp <sub>t</sub>	D <sub>o</sub> D <sub>p</sub>
<u>Ibuprofen</u>				
Diag 2	63 62	4.0 4.0	18 19	68 71
Diag 3	12 11	1.3 1.5	5 5	19 19
<u>Coproxamolc</u>				
Diag 1	57 56	6.1 6.3	40 40	63 62
Diag 3	5 4	1.2 1.4	5 5	9 8
<u>Paracodeine</u>				
Diag 1	50 49	5.8 5.9	40 41	56 55
Diag 3	3 3	1.1 1.3	5 5	6 6
<u>Piroxicam</u>				
Diag 1	36 31	4.3 5.0	39 42	39 39
Diag 3	8 7	1.2 1.4	5 5	12 13
<u>Indomethacin</u>				
Diag 1	43 29*	3.3 4.9*	40 42	48 47
Diag 3	16 15	1.4 1.5	5 5	27 25
<u>Mefenamic</u>				
Diag 1	36 36	5.3 5.2	42 42	41 39
Diag 2	16 14	2.3 2.6	23 21	19 17
mean	27 26	3.1 3.3	22 22	34 33
MAD	1.3	0.2	0.8	1.2

**Note:** MAD computed excluding entries marked with \*  
 o = Observed, t = Dirichlet Prediction,  
 p = Predicted from Duplication Coefficient.

Like the cardiovascular Nifedipine in diagnosis 1 (see the text in Section 7.4), Indomethacin in musculo-skeletal diagnosis 1 has a surfeit of light prescribers in a quarter compared to the Dirichlet predictions.







**Table 7A.6 Observed and Predicted Penetrations and Prescription Frequencies Musculo-skeletals - Diagnosis 1**

4 weeks	Diag Shr	$b_o$	$b_t$	$w_o$	$w_t$
Ibuprofen	18	47	55	4.2	3.6
Coproxamolc	11	38	39	3.0	3.0
Naproxen	10	35	36	3.1	3.0
Paracodeine	9	34	33	2.9	2.9
Mefenamic	6	22	24	2.9	2.7
Voltaren	5	22	20	2.3	2.6
Piroxicam	5	20	20	2.5	2.6
Indomethacin	4	24	18	2.0	2.6
Ketoprofen	2	8	8	2.3	2.4
All others	31	73	73	4.7	4.7

**Table 7A.7 Observed and Predicted Penetrations and Prescription Frequencies Musculo-skeletals - Diagnosis 2**

4 weeks	Diag Shr	$b_o$	$b_t$	$w_o$	$w_t$
Ibuprofen	16	39	40	2.1	2.1
Naproxen	10	28	28	1.9	1.9
Voltaren	9	25	26	1.9	1.9
Indomethacin	7	20	20	1.8	1.8
Piroxicam	7	19	20	1.8	1.8
Ketoprofen	6	15	17	2.0	1.7
Coproxamolc	5	17	15	1.5	1.7
Paracodeine	5	14	14	1.6	1.7
Mefenamic	2	8	8	1.6	1.6
All others	32	61	61	2.7	2.7

**Table 7A.8 Observed and Predicted Penetrations and Prescription Frequencies Musculo-skeletals - Diagnosis 3**

4 weeks	Diag Shr	b <sub>o</sub>	b <sub>t</sub>	w <sub>o</sub>	w <sub>t</sub>
Ketoprofen	6	3	4	1.3	1.2
Voltaren	9	5	5	1.2	1.2
Naproxen	10	6	6	1.2	1.2
Indomethacin	11	6	6	1.1	1.2
Ibuprofen	8	5	5	1.1	1.2
Piroxicam	5	3	3	1.1	1.1
Paracodeine	2	1	1	1.0	1.1
Coproxamolc	3	2	2	1.1	1.1
All others	48	21	23	1.6	1.5

**Table 7A.9 Observed and Predicted Penetrations and Prescription Frequencies Cardiovasculars - Diagnosis 1**

12 weeks	Diag Shr	b <sub>o</sub>	b <sub>t</sub>	w <sub>o</sub>	w <sub>t</sub>
Atenololc	23	61	62	3.2	3.1
Captopril	11	25	41	3.9	2.3
Nifedipine	9	37	34	1.9	2.1
Bendroflu.	7	29	30	2.1	2.1
Cyclopenth.	6	17	25	2.8	2.0
Propranolol	5	21	21	1.9	1.9
Frusemide	4	20	20	1.8	1.9
Spirolact.	2	9	9	1.9	1.7
Other	33	68	72	4.1	3.9

**Table 7A.10 Observed and Predicted Penetrations and Prescription Frequencies Cardiovasculars - Diagnosis 2**

12 weeks	Diag Shr	b <sub>o</sub>	b <sub>t</sub>	w <sub>o</sub>	w <sub>t</sub>
GTN	40	56	60	2.5	2.4
Nifedipine	18	34	39	1.9	1.7
ISMO	13	27	32	1.8	1.5
ISDIN	10	19	25	1.8	1.4
Atenololc	5	14	15	1.3	1.3
Propranolol	4	10	10	1.3	1.2
Verapamilc	1	4	4	1.3	1.2
Other	9	18	22	1.6	1.4

**Table 7A.11 Observed and Predicted Penetrations and Prescription Frequencies Cardiovasculars - Diagnosis 3**

12 weeks	Diag Shr	b <sub>o</sub>	b <sub>t</sub>	w <sub>o</sub>	w <sub>t</sub>
Frusamide	43	45	47	2.4	2.3
Bumetanide	12	17	21	1.8	1.4
Spirolact.	10	17	19	1.5	1.4
Digoxin	7	14	14	1.4	1.3
Cyclopenth.	5	8	9	1.5	1.2
Bendroflu.	4	8	9	1.4	1.2
Other	19	27	29	1.7	1.6

**Table 7A.12 Observed and Predicted Penetrations and Prescription Frequencies Cardiovasculars - Diagnosis 4**

12 weeks	Diag Shr	b <sub>o</sub>	b <sub>t</sub>	w <sub>o</sub>	w <sub>t</sub>
Propranolol	32	15	19	1.7	2.4
Digoxin	30	16	18	1.5	1.4
Verapamilc	10	5	7	1.5	1.2
Atenololc	7	4	5	1.4	1.1
Nifedipine	1	1	1	1.0	1.1
Other	20	13	13	1.3	1.3

**Table 7A.13 Observed and Predicted Penetrations and Prescription Frequencies Cardiovasculars - Diagnosis 5**

12 weeks	Diag Shr	b <sub>o</sub>	b <sub>t</sub>	w <sub>o</sub>	w <sub>t</sub>
Propranolol	10	5	6	1.4	1.3
Frusemide	10	5	6	1.4	1.3
Digoxin	5	2	3	1.3	1.3
Bumetanide	3	2	2	1.1	1.2
Atenololc	2	2	1	1.0	1.2
Other	70	26	30	2.0	1.7

**CHAPTER 8: PRESCRIBING OF BRANDS AND GENERICS****Summary****8.1 Introduction****8.2 Prescription Shares of Brands and Generics****8.3 Prescribing of Brands and Generics****8.4 Share of Requirements and Sole Prescribing****8.5 Modelling the Prescribing of Brands and Generics****8.6 Summarising the Fit of the Dirichlet****8.7 Brand and Generic Partitioning****8.8 Individual Brands and their Generic Equivalents****8.9 Conclusions****Appendices to Chapter 8**

### Summary

Overall, over 70% of prescriptions written in both product classes specify a branded drug with generics used for the balance. There is some variation according to product class and diagnosis (see table 8.5). In this sense, brands dominate prescribing behaviour.

There are more brands used than generics and the average brand's share of any diagnosis in either product class differs little from the average generic's share (see table 8.5).

Brands and generics are prescribed in similar ways. This is found to be true for brands and generics in general, for brands which have direct generic equivalents and for generics which do not have branded equivalents available on prescription. As a result, the Dirichlet models both brand and generic prescribing behaviour well.

The differences that do exist are largely predictable and dependent only on the share of prescriptions that the specific version commands. This is summarised by comparing the product of the average prescription frequency and the average proportion of non-prescribers for brands and generics.

**Table 8.1 Brands and Generics Compared**

12 Weeks	$w_{av}(1-b_{av})$ Brands	$w_{av}(1-b_{av})$ Generics
Musculo-skeletals	3.2	3.3
Cardiovasculars	1.5	1.6

Brands do account for a marginally higher percentage of their prescribers total requirements than do generics in cardiovascular prescribing, but the pattern is reversed in musculo-skeletals. Table 8.2 shows that the difference is very small indeed.

**Table 8.2 Brands and Generics:  
Average Share of Requirements**

	Average Share of Requirements Brands (%)	Average Share of Requirements Generics (%)
Musculo-skeletals	8	10
Cardiovasculars	6	5

The Dirichlet fits brands and generics equally well. Table 8.3 shows the average observed brand and generic penetration along with the average mean absolute deviation from the Dirichlet predictions for both product fields.

**Table 8.3 Brands and Generics: Comparing the Fit of  
Observed and Theoretical Penetrations**

	Musculo-skeletal (4 weeks)		Cardiovascular (12 weeks)	
	Average Brand	Average Generic	Average Brand	Average Generic
Penetrations (%) (Observed)	38	34	28	19
MAD from Dir. prediction	4.2	4.4	2.0	1.2

In addition to the brand Capoten there is another incidence of poor fit, this time it is the generic Ibuprofen. This is examined in Section 8.6.

Doctors who prescribe generics are more likely to prescribe other generics than are prescribers of brands to prescribe other brands. This effect is, however, small and not exclusive, so that there is a great deal of multi-format prescribing which occurs, just as there is a great deal of multi-entity prescribing. The extent of the resultant market partition is summarised by table 8.4

**Table 8.4 Duplication of Prescribing Between Brands and Generics**

48 Weeks	<u>% who also prescribe:</u>			
Prescribers of any:	Musculo-skeletal		Cardiovascular	
	Brand	Generic	Brand	Generic
Brand	1.08	1.06	1.20	1.12
Generic	1.03	1.30	1.12	1.30

At the level of the individual brand and its generic equivalent, doctors are less likely to prescribe the generic version if they also prescribe the branded form of the same drug when compared, on average, to prescribers of all the other entities. The pattern holds for all the musculo-skeletal diagnoses, but only some of the cardiovascular diagnoses. This pattern does not appear to be symmetrical, so that the proportion who prescribe the branded version and its specific generic equivalent is similar to the proportion of any of the entities also prescribing that specific generic.

### **8.1 Introduction**

In **Section 3.5** the aggregate patterns of prescribing brands and their generic equivalents were presented. These showed that once the size of the category was taken into account there seemed to be little difference, overall, in the way that brands and generics were prescribed. This chapter explores the patterns at the individual brand or generic level.

**Section 8.2** analyses the share of prescriptions accounted for by brands and their generic equivalents. This analysis covers both product fields and their diagnostic sub-categories showing that the prescribing of brands is dominant.

**Section 8.3** briefly reports some published views on the role of the brand in buyer behaviour and then compares penetration, and prescription frequencies for brands and generics. **Section 8.4** examines the share of requirements and sole prescribing accounted for by brands and generics. Both these sections reveal that brands are very similar to generics in terms of their prescribing patterns and that brands have no intrinsic strength apart from that accorded by prescription share.

**Section 8.5** successfully models these measures using the Dirichlet and **Section 8.6** provides a summary of the excellent fit of the model.

**Section 8.7** examines how the duplication coefficients for brand and generic prescription vary across diagnoses and product classes, in order to see whether any brand based market partitions are identifiable. A weak partition is found between prescribers of generics. Again this result is not consistent with conclusions which might be drawn from traditional theories of branding.

**Section 8.8** models and compares prescribing behaviour for some specific pairs of brands and their generic equivalent. Some conclusions end the chapter.

Where periods of less than one year are used in the analysis in this chapter, they are averages of twelve separate months or four separate quarters.

## **8.2 Prescription Shares of Brands and Generics**

In heart disease, doctors are free to prescribe any licensed drug in any form they choose. They can write a brand or a generic name on the prescription and so if the specific drug is still protected by patent, then the patient will receive the brand irrespective of the form specified by the prescription. Thus if the doctor wrote 'Atenolol' (a generic name) on the prescription the pharmacist would dispense

Tenormin (the brand). If, however, the doctor wrote 'Spironolactone' on the prescription, the patient could receive any one of 6 brands of chemical equivalence as Spironolactone without patent protection is marketed by several pharmaceutical suppliers under different brand names.

At the time when the data were collected, cardiovascular products were all branded, and many were patent protected. In the case of the current research there are, therefore, four alternative outcomes:

The doctor prescribes -

1. A patented chemical by the brand name which results in the dispensing of the brand.
2. A patented chemical by the generic name which results in the dispensing of the brand.
3. A non-patented chemical by the brand name which results in the dispensing of that specific brand.
4. A non-patented chemical by the generic name which results in the dispensing of a brand, determined by the pharmacist.

In the case of musculo-skeletal these same four outcomes are possible, but in addition, there are some chemical entities which are not patent protected and are available from generic suppliers. This means that if the doctor prescribes a chemical by generic name, the pharmacist could either dispense a brand or a generic version of the product. Finally, there are some chemicals which are only available by NHS prescription in generic form.

Table 8.5 lists the share of prescriptions which specify a brand or a generic name and shows that about a third of all musculo-skeletal prescriptions are generic. On the other hand, only just over 10% of cardiovascular prescriptions are generic. The degree of generic prescribing also varies according to the diagnosis, with the miscellaneous category

for musculo-skeletal having the highest incidence of generic prescribing.

**Table 8.5 Brand and Generic Prescription Shares**

	Brand Total Share (%)	Generic Total Share (%)	Average Brand Share (%)	Average Generic Share (%)
Musculo-skeletal	72	28	4.0	3.7
Miscellaneous (D1)	67	33	4.0	5.4
Rheumatoid Arthritis (D2)	79	21	5.5	2.7
Osteo-arthritis (D3)	83	17	5.2	2.0
Cardiovasculars	89	11	3.7	2.5
Hypertension (D1)	87	13	4.9	3.6
Angina (D2)	94	6	6.4	2.4
Heart Failure (D3)	85	15	8.8	7.1
Arrhythmia (D4)	85	15	14.1	7.3
Other (D5)	93	7	4.1	2.2

The fact that brands and generics command such different shares suggests comparison of the way they are prescribed. This is the subject of the following section.

### **8.3 Prescribing of Brands and Generics**

There is a received belief in marketing that successful branding confers competitive advantage due to customer loyalty. Blackett (1989), for example, claims that long established brands which command consumer loyalty are 'particularly valuable'. In contrast, Howard (1989) describes data claiming that brand leaders attract lower loyalty levels than some smaller brands which he describes as practicing "segmented marketing" whereas the brand leaders practise "mainstream marketing". He states that

'These are obviously two radically different ways of marketing, and the manager must be aware as to which one he is practicing in order to practice it consistently and effectively'

p. 91

Howard also believes that high brand loyalty is typical in markets which are mature and where growth has levelled off (p. 93). It should be pointed out that there is much accumulated evidence to refute this view (eg Ehrenberg, 1988) and that in general it is large brands which attract higher levels of loyalty than small ones. This evidence also challenges Howard's assertion that segmentation and mainstream marketing are 'obviously two radically different ways of marketing'.

Morwind (1987) is another writer who believes that loyalty plays an important role in consumer behaviour:

'...consumers today must rely more on brand reputations as a base source for information. Purchasers must use a buying pattern that involves selecting brand names. The fact that this is already happening helps explain why, in many categories, brand loyalty is rising.' p. 179.

Baker (1992) sees an economic rationale for focussing on loyal customers:

'...it has been estimated that as a working rule of thumb it costs six times as much money to win a new customer as to retain an existing customer's loyalty' p. 230

This view is consistent with that of Leavitt (1983) who cites the Proctor & Gamble advisory service designed to give advice on products and their usage resulting in 'raised customer brand loyalty' (p. 115). Here again, however, the accumulated evidence of analysing buyer behaviour challenges the concept of maintaining or increasing sales by winning new customers as opposed to maintaining existing ones. Instead, markets are characterised by buyers with varying frequencies of purchase, but the brands they buy show only small and predictable differences in the way they are bought (Ehrenberg and Goodhardt, 1979).

The very process of branding is an attempt in some way or other to convey and reinforce a set of benefits which is

distinct from competition. If branding works in this way, one would expect to find differences in the ways that brands are purchased when compared to non-branded items. For example, given a brand and a generic with equal market share one would expect the brand to be purchased more frequently by a smaller number of buyers than the generic. That is, it commanded higher loyalty and achieved its sales level by appealing to a smaller number of customers than the generic version. As a result one might expect the brand to account for a larger share of the customer's product class needs than a generic version would. Further, one might expect to see higher levels of sole buying for brands than generics and also see higher buying frequencies for sole buyers of brands when compared to generics. Finally, one might also expect buyers of brands to be more likely to buy other brands to satisfy other needs than buyers of generics would buy other generics.

In previous buyer behaviour research it has not been possible to directly explore the 'power' of brands except in comparison to other brands and in one instance to store brands (Ellis, 1989). In the current research, the way that doctors prescribe brands and generics is directly observable from the data collected.

Table 8.6 shows market shares, penetrations and prescription frequencies for a selection of brands and generics in the musculo-skeletal product class, and table 8.7 shows the same data for some cardiovasculars. To distinguish between the two forms, generics are listed in upper case.

In the case of musculo-skeletals, table 8.6 shows the familiar 'Double Jeopardy' pattern which holds (with some exceptions) for brands and generics alike. In many cases it would not be possible to distinguish between the forms without prior identification. The brand Froben and the generic Cocodamol both have market shares of just under 3% and they are both prescribed by one third of doctors an

**Table 8.6 Musculo-skeletal Penetration  
and Prescription Frequencies**

12 weeks	MS (%)	b(%)	w
Brufen	11.0	67	8
COPROXAMOL	8.4	61	7
Naprosyn	6.6	56	6
Voltarol	6.1	55	6
Feldene	5.1	50	5
IBUPROFEN*	(4.9)	(22)	(11)
Ponstan	4.4	38	6
CODYDRAMOL	3.7	37	5
Indocid	3.6	49	4
Lederfen	3.1	38	4
Froben	2.9	31	5
COCODAMOL	2.9	31	5
PARACETAMOL	2.9	47	3
Oruvail	2.9	29	5
Surgam	2.7	29	5
Movelat	2.6	21	6
Synflex	2.1	17	6
Rheumox	1.9	22	4
INDOMETHACIN	1.6	18	4
Benoral	1.5	26	3
NAPROXEN	1.5	14	5
Av. Brand	4.0	38	5
Av. GENERIC*	3.7	34	5
Av. All*	3.9	37	5

Note: \* Averages exclude IBUPROFEN

average of just under five times in a quarter. The biggest deviation from the overall pattern occurs for the generic Ibuprofen which has the highest average prescription frequency in the product class - by comparison with the other brands and generics its prescription frequency is about double the norm for its market share. It should be noted that in this chapter Ibuprofen is treated separately from the branded version Brufen, whereas in chapters 6 and 7 the two forms are combined and analysed as one entity.

**Table 8.7 Cardiovascular Penetration and Prescription Frequencies**

12 weeks	MS (%)	b (%)	w
Adalat	7.1	49	2
Tenormin	5.3	37	2
Capoten*	(4.8)	(19)	(4)
Cyclopen	3.9	22	3
ATENOLOL	3.8	26	2
Moduretic	3.6	28	2
BENDROFLUAZIDE	3.2	24	2
Inderal	3.1	25	2
Digoxin	2.9	28	2
Innovace	2.6	19	2
Frumil	2.6	22	2
Burinex	2.4	21	2
PROPRANOLOL	2.2	18	2
FRUSEMIDE	2.1	20	2
METHYLDOPA	1.8	15	2
NIFEDIPINE	1.7	14	2
Av. Brand*	3.7	28	2
Av. GENERIC	2.5	19	2
Av. All*	3.2	24	2

Note: \* Averages exclude Capoten

If traditional thinking about branding were correct, one would expect the opposite pattern to hold, with generics having lower prescription frequencies than brands. Table 8.6 shows that with the exception of Paracetamol, generics are prescribed with at least the same frequency as brands for musculo-skeletal and usually, it seems, with a higher frequency than brands, for a given prescription share.

Table 8.7 shows the picture for cardiovasculars, and here there seems to be no difference in the way that brands and generics are prescribed, with the exception of the brand Capoten. This has already been noted, and is the subject of further analysis in Chapter 9.

One simple way of demonstrating the similarities between brands and generics is to use a summary measure from analysing brands and using it to predict some aspect of generic prescribing behaviour. Ehrenberg, Goodhardt and Barwise (1990) utilise the lawlike relationship  $w_x(1-b_x) = w_y(1-b_y)$  for a product class. This states that the average prescription frequency of a brand multiplied by the proportion of non-prescribers is approximately constant. This constant for musculo-skeletal brands is calculated by averaging the quantity  $w(1-b)$  across all the brands in table 8.6 to give a value of  $w_0 = 3.2$ . This constant can then be used to predict the average prescription frequency of the generics knowing only the number of prescribers of each generic. The results along with the actual prescription frequencies are shown in table 8.8.

**Table 8.8 Predicting Musculo-skeletal Prescription Frequencies for Generics**

12 Weeks GENERIC	$w_0/(1-b)$	$w(\text{Obs})$
COPROXAMOL (IBUPROFEN) *	8 (4)	7 (11)
CODYDRAMOL	5	5
COCODAMOL	5	5
PARACETAMOL	6	3
INDOMETHACIN	4	4
NAPROXEN	4	5
Average*	5	5

Note: \* Average exclude IBUPROFEN

The average at the foot of table 8.8 shows the close overall fit of a very simple predictive model and therefore the similarity between musculo-skeletal brands and generics. A similar result was obtained with cardiovasculars.

The analysis thus far shows the picture at the aggregate level, but table 8.5 showed that there are differences in generic shares according to diagnosis and it was therefore appropriate to extend the analysis to the lower level of

aggregation. For clarity of presentation, detailed discussion of these results are omitted as the patterns were consistent with those described above. In all cases it would be impossible to distinguish between brands and their generic equivalents without prior identification in the tables. One conclusion is that the differences in the way that brands and generics are prescribed are explained simply by the share of prescriptions they attract.

A selection of the tables which were prepared covering other diagnoses are included in the appendix to this chapter (Tables 8A.1 - 8A.4), representing those with large and small generic shares of both product fields.

#### **8.4 Share of Requirements and Sole Prescribing of Brands and Generics**

Having found no substantive difference in the average rate of prescribing brands and generics, there are two key areas where the traditional view of branding might lead to other differences between the two product forms. Firstly, brands might account for higher proportions of their prescribers total needs when compared to generics. Secondly, one might expect to see generics with fewer sole prescribers and lower rates of sole prescribing than a brand of comparable market share.

Table 8.9 shows the share of requirements accounted for by brands and generics in the cardiovascular product field. The averages at the foot of the table show that again brands and generics account for a similar share of their users total prescribing needs. The same pattern is found for musculo-skeletal and so the detail is not reported here.

At the product class level, the incidence of sole prescribing is very low indeed, and therefore it is more illuminating to examine the data at the diagnosis level.

**Table 8.9 Cardiovasculars - Share of Requirements**

12 weeks	MS (%)	Share of Requirements (%)
Adalat	7.1	11
Tenormin	5.3	10
Capoten*	(4.8)	(15)
Cyclopen	3.9	12
ATENOLOL	3.8	11
Moduretic	3.6	8
BENDROFLUAZIDE	3.2	9
Inderal	3.1	9
Digoxin	2.9	7
Innovace	2.6	9
Frumil	2.6	8
Burinex	2.4	8
PROPRANOLOL	2.2	9
FRUSEMIDE	2.1	7
METHYLDOPA	1.8	7
NIFEDIPINE	1.7	9
Av. Brand*	3.7	9
Av. GENERIC	2.5	9
Av. All	3.2	9

Note: \* Av. Brand excludes Capoten

Table 8.10 shows the proportion of sole prescribers and the average prescription frequency of the sole prescriber along with the overall average prescription frequency as a comparison, for rheumatoid arthritis. Tables 8A.5 - 8A.7 in the appendix show the same data for Arrhythmia, Heart Failure and 'Other' cardiovascular diagnoses.

There are three main patterns which emerge from this analysis of sole-prescribing. Firstly, brands do not attract larger numbers of sole prescribers than generics. Secondly, sole prescribers of brands do not prescribe more frequently than sole prescribers of generics. Thirdly, average sole prescribing rates are the same or lower than the average rates of prescribing and this is true for both brands and generics alike.

**Table 8.10 Rheumatoid-Arthritis - Sole Prescribing**

4 weeks	MS (%)	bs (%)	ws	w
Brufen	11.6	7	1.6	2.1
Voltarol	8.9	8	1.4	1.9
Naprosyn	8.4	7	1.8	1.9
Feldene	6.6	6	1.5	1.9
Oruvail	5.6	5	2.3	2.1
Indocid	5.3	5	1.7	1.8
Lederfen	5.2	8	1.4	1.8
COPROXAMOL	4.9	3	1.4	1.5
Surgam	4.2	8	1.8	1.8
Froben	3.8	4	1.4	1.8
IBUPROFEN	3.7	11	1.4	2.0
PARACETAMOL	2.8	4	1.1	1.4
Benoral	2.4	4	1.3	1.5
Ponstan	2.3	3	1.8	1.6
Rheumox	2.2	6	3.0	1.6
CODYDRAMOL	2.2	3	1.3	1.5
COCODAMOL	2.0	2	1.5	1.6
NAPROXEN	1.7	7	1.1	1.6
INDOMETHACIN	1.4	7	1.6	1.6
Av. Brand	5.5	6	1.8	1.8
Av. GENERIC	2.7	5	1.3	1.6
Av. All	4.5	6	1.6	1.7

Table 8.10 does provide two examples where sole prescribing rates exceed the overall rate, the most striking being the brand Rheumox. The relatively high sole prescribing rate is explained by the fact that during the year only 10 incidents of sole prescribing in any of the twelve months occurred. Of these 10, four were different doctors prescribing the brand at above the average rate. In two cases the doctors prescribed the brand 3 times and in the other two cases the prescription frequency was 5 times in the month. The sole prescribing rate here is, therefore, not a significant deviation from the overall pattern which is repeated in the other diagnoses shown in the appendix to the chapter.

### 8.5 Modelling the Prescribing of Brands and Generics

In Chapter 6 the Dirichlet was used to model and predict aspects of prescribing behaviour and the same approach is adopted here to examine the ability of the model to describe brand and generic prescribing behaviour. Tables 8.11 and 8.12 show the observed and Dirichlet predictions for penetrations and prescription frequencies and again the generics are shown in upper case.

**Table 8.11 Modelling Musculo-skeletal Penetration and Prescription Frequencies**

12 weeks	MS (%)	b (%)		w	
		O	T	O	T
Brufen	11.0	67	73	8	8
COPROXAMOL	8.4	61	65	7	7
Naprosyn	6.6	56	57	6	6
Voltarol	6.1	55	54	6	6
Feldene	5.1	50	48	5	5
IBUPROFEN*	(4.9)	(22)	(46)	(11)	(5)
Ponstan	4.4	38	44	6	5
CODYDRAMOL	3.7	37	38	5	5
Indocid	3.6	49	38	4	5
Lederfen	3.1	38	34	4	5
Froben	2.9	31	32	5	5
COCODAMOL	2.9	31	32	5	5
PARACETAMOL	2.9	47	31	3	5
Oruvail	2.9	29	31	5	5
Surgam	2.7	29	30	5	5
Movelat	2.6	21	29	6	5
Synflex	2.1	17	24	6	4
Rheumox	1.9	22	23	4	4
INDOMETHACIN	1.6	18	19	4	4
Benoral	1.5	26	19	3	4
NAPROXEN	1.5	14	18	5	4
Av. Brand	4.0	38	38	5	5
Av. GENERIC*	3.5	34	34	5	5
Av. All	3.9	37	37	5	5
MAD Brand		4.2		0	
MAD GENERIC*		4.4		0	
MAD All*		4.3		0	
r <sup>2</sup> All*		0.86			

Note: \* Summary measures exclude IBUPROFEN

**Table 8.12 Modelling Cardiovascular Penetration and Prescription Frequencies**

12 weeks	MS (%)	b(%)		w	
		O	T	O	T
Adalat	7.1	49	46	2	2
Tenormin	5.3	37	37	2	2
Capoten*	(4.8)	(19)	(35)	(4)	(2)
Cyclopen	3.9	22	30	3	2
ATENOLOL	3.8	26	28	2	2
Moduretic	3.6	28	28	2	2
BENDROFLUAZIDE	3.2	24	25	2	2
Inderal	3.1	25	24	2	2
Digoxin	2.9	28	24	2	2
Innovace	2.6	19	21	2	2
Frumil	2.6	22	21	2	2
Burinex	2.4	21	20	2	2
PROPRANOLOL	2.2	18	18	2	2
FRUSEMIDE	2.1	20	17	2	2
METHYLDOPA	1.8	15	15	2	2
NIFEDIPINE	1.7	14	14	2	2
Av. Brand*	3.7	28	28	2	2
Av. GENERIC	2.5	19	19	2	2
Av. All*	3.3	24	24	2	2
MAD Brand*		2.0		0.1	
MAD GENERIC		1.2		0.1	
MAD All*		1.7		0.1	
r <sup>2</sup> All		0.91			

**Note:** \* Summary measures exclude Capoten

Tables 8.11 and 8.12 show that the Dirichlet provides a good fit to the data for brands and generics with a few exceptions, the most significant (as already noted) being Ibuprofen and Capoten. Excluding these entities, the Dirichlet predicts penetrations and average prescribing rates well as shown by the mean absolute deviations towards the foot of both tables. The high r-squared values for the fit between observed and predicted penetrations provide a simple summary measure of fit.

Here the Dirichlet provides norms which allow a measure of the deviation for the two exceptions. Ibuprofen is prescribed twice as frequently and by half the doctors for its market share and Capoten is similar in numerical terms. Table 8.12 shows that Cyclopentiazide has a lower than predicted penetration and table 8.11 shows that Indocid has a higher than predicted penetration. Both these were also noted in Chapter 6. The other main deviation to note in the two product classes is Paracetamol in table 8.11. This generic has more prescribers than predicted by the Dirichlet.

Table 8.11 is also interesting in that it shows data for four formulations which doctors can only prescribe by generic name. Coproxamol, Codydramol, Cocodamol and Paracetamol are all analgesics which were subject to the first limited list and therefore the pharmacist dispenses the cheapest available product.

For three out of the four 'limited' generics, the Dirichlet predicts penetration and prescription frequency very well. Indeed Paracetamol is the exception as noted above. Again, the implication is that the imposition of restrictions does not affect the way that doctors prescribe drugs and that it is the overall share of prescriptions which determine loyalty levels and nothing intrinsic about the specific product.

Tables 8A.8 - 8A.11 in the appendix to the chapter show the observed and predicted penetration and prescription frequencies for two musculo-skeletal and two cardiovascular diagnoses with differing shares of generic prescribing. It is clear that the Dirichlet succeeds in modelling both brand and generic prescribing at the diagnosis level.

Table 8.13 shows the fit between observed and theoretical shares of requirements for the cardiovascular product field and table 8.14 shows the fit for sole prescribing in the

Rheumatoid Arthritis diagnosis of the musculo-skeletal product class.

**Table 8.13 Cardiovascular - Share of Requirements**

12 weeks	MS (%)	Observed Share of Requirements (%)	Theoretical Share of Requirements (%)
Adalat	7.1	11	11
Tenormin	5.3	10	10
Capoten*	(4.8)	(15)	(10)
Cyclopen	3.9	12	9
ATENOLOL	3.8	11	9
Moduretic	3.6	8	9
BENDROFLUAZIDE	3.2	9	9
Inderal	3.1	9	8
Digoxin	2.9	7	8
Innovace	2.6	9	8
Frumil	2.6	8	8
Burinex	2.4	8	8
PROPRANOLOL	2.2	9	8
FRUSEMIDE	2.1	7	8
METHYLDOPA	1.8	7	8
NIFEDIPINE	1.7	9	8
Av. Brand*	3.7	9	9
Av. GENERIC	2.5	9	8
Av. All	3.2	9	9
MAD Brand*			0.8
MAD GENERIC			1.0
MAD All*			0.9

Note: \* Av. Brand excludes Capoten

The fit between the observed and predicted share of requirements is very close and the empirical observation that brands and generics do not differ in this respect is predicted from the Dirichlet.

**Table 8.14 Rheumatoid-Arthritis - Sole Prescribing**

4 Weeks	MS (%)	bs (%)		ws	
		O	T	O	T
Brufen	11.6	7	6	1.6	1.5
Voltarol	8.9	8	6	1.4	1.4
Naprosyn	8.4	7	6	1.8	1.4
Feldene	6.6	6	6	1.5	1.4
Oruvail	5.6	5	5	2.3	1.4
Indocid	5.3	5	5	1.7	1.4
Lederfen	5.2	8	5	1.4	1.4
COPROXAMOL	4.9	3	5	1.4	1.2
Surgam	4.2	8	5	1.8	1.3
Froben	3.8	4	5	1.4	1.3
Ibuprofen	3.7	11	4	1.4	1.2
PARACETAMOL	2.8	4	4	1.1	1.2
Benoral	2.4	4	5	1.3	1.3
Ponstan	2.3	3	5	1.8	1.3
Rheumox	2.2	6	5	3.0	1.3
CODYDRAMOL	2.2	3	4	1.3	1.2
COCODAMOL	2.0	2	4	1.5	1.2
NAPROXEN	1.7	7	4	1.1	1.2
INDOMETHACIN	1.4	7	4	1.6	1.2
Av. Brand	5.5	6	5	1.8	1.5
Av. GENERIC	2.7	5	4	1.3	1.5
Av. All	4.5	6	5	1.6	1.5
MAD Brand		1.3		0.4	
MAD GENERIC		2.4		0.2	
MAD All		1.7		0.3	

The fit with sole prescribing frequency here is also good and where the fit with the proportion of sole prescribers is sometimes less close, this is due to low penetrations. Other examples of the Dirichlet fitted to sole prescribing at the diagnosis level are found in tables 8A.12-8A.14 in the appendix to this chapter and in table 8A.14 the Dirichlet predicts that 56% of Inderal prescribers will use only that brand in a month, whereas the actual number is 77%. In a month however, Inderal's penetration in this diagnosis is only 1.2% or 3 doctors and it can be seen that the difference in practical terms is negligible.

### 8.6 Summarising the Fit of the Dirichlet at the Diagnosis Level

In order to summarise the fit of the model, mean absolute deviations between the observed and Dirichlet predictions of penetration and prescription frequency were calculated for the eight diagnoses. These are shown in table 8.15.

Tables 8A.12 - 8A.14 in the appendix show the observed and Dirichlet predictions for sole prescribing in the other diagnoses.

**Table 8.15 Summarising the Fit of the Dirichlet**

	M.A.D. Avg. b b(O)	M.A.D. Avg.. w w(O)	No of brands/ generics
Musculo-skeletals (4 weeks)	2.6 23	0.3 2.8	19*
'Other' Musculo. Rheumatoid Arthritis	2.5 18 0.9 13	0.4 2.6 0.1 1.7	16* 19
Osteo-Arthritis	0.3 3	0.1 1.2	19
Cardiovasculars (12 weeks)	1.6 24	0.1 2.2	15 <sup>+</sup>
Hypertension	1.6 18	0.2 2.2	14 <sup>+</sup>
Angina	1.6 16	0.2 1.6	6
Heart Failure	0.9 13	0.1 1.5	7
Arrhythmia	0.5 6	0.1 1.5	7
Miscellaneous	0.3 2	0.2 1.3	15
Average	1.3 14	0.2 1.9	

\* M.A.D. excludes IBUPROFEN

+ M.A.D. excludes Capoten

Table 8.15 shows that overall the Dirichlet predicts penetrations and prescription frequencies very well and because its performance is similar when used with either brands or generics, only the overall averages are reported here.

One interesting fact concerns the prescribing behaviour associated with the generic Ibuprofen. Table 8.11 showed that Ibuprofen had just under half the number of doctors prescribing twice as frequently as predicted by the Dirichlet. Table 8A.8 (appendix) shows that this pattern is

also found for Ibuprofen when prescribed for 'Other' musculo-skeletal problems. Table 8.16 shows some prescribing behaviour data for Ibuprofen in all three diagnoses and indicates that prescribing behaviour is largely as expected for the other two diagnoses, and so the discrepancy is one restricted to a specific diagnostic situation.

**Table 8.16 Prescribing of Ibuprofen**

4 Weeks	MS (%)	b (%)				bs (%)			
		O T		O T		O T		O T	
'Other'	5.6	14	25	4.4	2.5	3	2	1.6	1.4
Rheum. Arthritis	3.7	10	12	2.0	1.5	11	4	1.2	1.2
Osteo-arthritis	1.4	1	1	1.1	1.1	67	35	0.9	1.0

It would be useful to repeat the analysis in subsequent years to see whether this pattern held consistently.

### **8.7 Brand and Generic Partitioning**

One test of the power of branding is to examine how likely a prescriber of one brand is to prescribe another. If brands appeal to a definable section of doctors then this should be observable in duplication tables. It would then be simple to repeat the analysis with prescribers of generics. If branding has a strong effect then the duplications between prescribers of brands should be greater than those between prescribers of generics.

Duplication coefficients are calculated by taking an average rate of duplication and dividing by the penetration of a brand or generic. A coefficient of about 1 means that prescribing can be described as an independent process, which is one of the key assumptions underlying the Dirichlet model. Section 6.8 showed that this is the case for prescribing at the aggregate product class level.

Table 8.17 lists the duplication coefficients calculated for the two product fields along with the average penetrations

for brands and generics. For the analyses in this section, duplications were calculated for a total of 43 cardiovascular entities and 59 musculo-skeletal. Table 8A.15 (appendix) shows the breakdown between brands and generics for the two product classes and the eight diagnoses.

**Table 8.17 Duplication of Prescribing Between Brands and Generics**

48 Weeks	<u>% who also prescribe:</u>			
	Musculo-skeletal		Cardiovascular	
Prescribers of any:	Brand	Generic	Brand	Generic
Brand	1.08	1.06	1.20	1.12
Generic	1.03	1.30	1.12	1.30
Average Penetration (%)	36	24	37	40

Table 8.17 shows that there is a weak partition between brands and generics in both product fields over the course of a year. Prescribers of generics are more likely to prescribe other generics than they are other brands. They are also more likely to prescribe other generics than prescribers of brands are likely to specify other brands. This is the opposite pattern that might be predicted by a traditional view of branding, and indicates that if anything, there is a slight tendency for generic proneness in prescribing. The extent of the effect could be measured by analysing data in subsequent years in the UK where budgetary and environmental changes are understood to have increased the overall level of generic prescribing. In addition, if similar data available were from a country such as the USA which operates without the level of prescription subsidy the partitioning effect could be compared.

The size of the partitioning effect needs quantifying in practical terms. To illustrate, it is assumed that there are two musculo-skeletal (MG1 and MG2) which have the average

generic annual penetration of 24% and two brands (MB1 and MB2) with a 36% annual penetration.

The number of doctors prescribing both MG1 and MG2 would be predicted as  $1.3 \times .24 \times 243 = 76$  doctors and the number prescribing both MB1 and MB2 would be  $1.08 \times .36 \times 243 = 94$  doctors. Because more brands have higher penetrations the overlaps will be higher in absolute terms despite the partition. In addition, because the maximum duplication is 100%, only generics with a penetration below 75% in a year will show the excess of duplicate prescribers compared to a brand of similar penetration.

For cardiovasculars, the size of the partition is even smaller in a year, but the same broad conclusions can be drawn.

This analysis at the product class level could mask different partitioning effects at the diagnosis level and so the analysis was conducted to calculate the respective duplication coefficients. These are shown in tables 8A.16 - 8A.23 in the appendix to the chapter.

In the three musculo-skeletal diagnoses the pattern is consistent with similar partitions evident. In the case of cardiovasculars however, only the two biggest diagnoses have a generic partition. For 'Heart Failure' and 'Arrhythmia' the pattern is reversed and for 'Other' cardiovasculars there is no detectable partition at all.

The duplications for brands and generics are all close to 1 and therefore at a first approximation, the prescribing of one form of drug is independent of prescribing another. This is consistent with Dirichlet theory.

### **8.8 Individual Brands and their Generic Equivalents**

In Section 4.9 duplications between individual brands and their generics were examined at the product class level. It

was found that if a doctor prescribed one form of the drug they were less likely to prescribe the other form than the population as a whole. The effect was observable but not absolute, and there were two instances (Brufen/Ibuprofen and Frumil/Frusemide) where there appeared to be no partitioning. In this section the analyses of Section 4.9 are repeated at the diagnosis level to see whether the patterns are consistent, but first some measures of prescribing behaviour are examined in tables 8.18-8.19 to see how the Dirichlet fits data for specific brands and their direct generic equivalents.

**Table 8.18 Prescribing of Individual Brands and their Generic Equivalents - Rheumatoid Arthritis**

12 weeks	MS (%)	b(%)		w		wp	
		O	T	O	T	O	T
Brufen	11.6	50	51	3.6	3.5	19	19
IBUPROFEN	3.7	16	21	3.6	2.7	18	20
Naprosyn	8.4	41	41	3.2	3.2	20	20
NAPROXEN	1.7	10	11	2.7	2.5	20	20
Voltarol	8.9	43	43	3.2	3.2	19	19
Diclofenac	0.5	2	2	4.1	2.3	17	20
Indocid	5.3	31	29	2.6	2.8	21	20
INDOMETHACIN	1.4	9	9	2.3	2.5	19	21
Feldene	6.6	35	34	2.9	3.0	20	20
PIROXICAM	0.4	4	3	1.4	2.3	20	20
Lederfen	5.2	30	28	2.7	2.8	19	20
FENBUFEN	0.2	2	2	2.2	2.3	22	20
Froben	3.8	22	22	2.7	2.7	22	20
FLURBIPROFEN		.4	.2	1.0	1.6	15	14
Av. Brand	7.1	36	35	3.0	3.0	20	20
Av. GENERIC	0.7	5	5	2.3	2.3	19	19
Av. All	4.5	21	21	2.7	2.7	20	20

Tables 8.18 and 8.19 show quite clearly that brands differ from their generic equivalents only in that they have a higher prescription share. Brands do not differ from their generic equivalents in terms of the product class

prescribing rates of the doctors who use them. The results for the other diagnoses are found in tables 8A.24 - 8A.28 in the appendix to the chapter.

**Table 8.19 Prescribing of Individual Brands and their Generic Equivalents - Hypertension**

12 weeks	MS (%)	b(%)		w		wp	
		O	T	O	T	O	T
Tenormin	8.7	33	33	2.2	2.2	12	14
ATENOLOL	5.9	22	23	2.3	2.1	13	14
Adalat	6.9	32	27	1.8	2.1	12	14
NIFEDIPINE	1.8	7	8	2.0	1.8	15	15
Inderal	2.6	13	12	1.7	1.8	16	15
PROPRANOLOL	2.1	10	10	1.8	1.9	15	14
Av. Brand	6.1	26	24	1.9	2.0	13	14
Av. GENERIC	3.3	13	14	2.0	1.9	14	14
Av. All	4.7	20	19	2.0	2.0	14	14

In all diagnoses and cases the brand is prescribed by more doctors, more frequently than the generic equivalent, and in this way brands can be considered 'stronger' than their generic equivalents. Prescription share though, is the only difference, and if generic prescribing becomes more popular then the patterns of prescribing would change but in a highly predictable way.

In Section 8.7 a weak partition was found for generic prescribers. It is interesting to develop this approach to looking at the tendency of doctors who prescribe the branded form of a particular drug to also prescribe the generic equivalent and vice versa.

Table 8.20 shows part of the duplication table for the 'Other' musculo-skeletal diagnosis in order to describe the calculation of a measure which describes the propensity of a

doctor who prescribes the brand to also prescribe its generic equivalent.

**Table 8.20 Duplication of Prescribing -  
'Other' Musculo-skeletal**

48 Weeks Prescribers of:	% who also Prescribe:	
	Brufen	IBUPROFEN
Brufen		28
IBUPROFEN	69	
Naprosyn	81	31
NAPROXEN	70	70
Indocid	84	26
INDOMETHACIN	71	62
Voltarol	77	31
Diclofenac	67	89
Feldene	82	31
Piroxicam	67	83
Lederfen	79	30
Fenbufen	70	70
Froben	80	34
Flurbiprofen	67	83
Average Dup. Penetration	75	47
Dup. Coeff.	1.0	1.6
Dup. Coeff'.	0.9	0.9

Looking at the first column of the table it can be seen that on average 75% of the prescribers of any of the brands and generics also prescribe Brufen. This provides the duplication coefficient of 1.0 (rounded) when divided by Brufen's penetration at the foot of the table. Brufen however, is prescribed by 69% of the prescribers of Ibuprofen yielding the specific duplication coefficient of 0.9 (rounded). The percentage difference between these two coefficients is minus 7% meaning that a doctor who prescribes Ibuprofen (the generic) is 7% less likely to also prescribe Brufen (the branded equivalent) than a prescriber of any other entity. The corresponding data for Ibuprofen indicates that a prescriber of the branded version is 40% less likely to also prescribe the generic version than a prescriber of any other entity.

Table 8.21 shows the figures for other brand/generic pairs in the different musculo-skeletal diagnoses, and table 8.22 shows the same data for cardiovasculars.

**Table 8.21 Propensity to Prescribe Brands and their Generic Equivalents - Musculo-skeletal**

48 Weeks	'Other' Musculo.	Rheumatoid Arthritis	Osteo-Arthritis
	Relative Propensity to Prescribe the Other, Version by Prescribers of:	Relative Propensity to Prescribe the Other, Version by Prescribers of:	Relative Propensity to Prescribe the Other, Version by Prescribers of:
Brufen IBUPROFEN	- 7    -42	- 2    -46	-34    -47
Naprosyn NAPROXEN	-12    -51	1    -40	-29    -73
Voltarol Diclofenac	-10    -58	-12    -70	-29    -85
Indocid INDOMETHACIN	- 7    -36	15    -39	-41    -73
Feldene Piroxicam	- 9    -60	- 5    -56	
Lederfen Fenbufen	42    -27	16    -23	
Froben Flurbiprofen	-19    -61	3    -57	
Avg Brand	-48	-47	-70
Avg. Generic	- 2	2	-33

**Table 8.22 Propensity to Prescribe Brands and their Generic Equivalents - Cardiovasculars**

48 Weeks	Hyper-tension	Angina	Heart Failure/ Arrythmia
	Relative Propensity to Prescribe the Other Version by Prescribers of:	Relative Propensity to Prescribe the Other Version by Prescribers of:	Relative Propensity to Prescribe the Other Version by Prescribers of:
Adalat NIFEDIPINE	19 - 9	-28 -24	
Tenormin ATENOLOL	-19 -19	-18 -18	
Inderal PROPRANOLOL	24 31	30 13	-30 -17
Frumil FRUSEMIDE			-12 - 7
Avg Brand Avg. Generic	6 1	- 4 -10	-21 -12

Table 8.21 shows that in the case of musculo-skeletal, if a doctor prescribes the branded version of a drug, then they are less likely to also prescribe the generic version of the same drug than a prescriber of any of the other entities. The effect is largest for osteo-arthritis but for Rheumatoid Arthritis and 'Other' Musculo-skeletal complaints, the doctor who prescribes the brand is about 50% less likely to also prescribe the generic version. Looking at prescribers of a particular generic, a similar but smaller effect is noted for Osteo-arthritis. For 'Other' musculo-skeletal and Rheumatoid Arthritis, there is on average virtually no difference in the probability that a doctor will also prescribe the branded version compared to a prescriber of any of the other entities.

Table 8.22 shows a similar analysis for cardiovasculars and for Hypertension and Angina, there is less consistency than for musculo-skeletal. For example, prescribers of

Propranolol are more likely to also prescribe the branded version Inderal than prescribers of an average entity in the diagnosis. In the case of Heart Failure and Arrhythmia there is a lower than average propensity in both cases, but the order is reversed from the other diagnoses.

### 8.9 Conclusions

This chapter provides results which question the power that some marketers confer on brands. The current research provides an opportunity to compare directly the prescribing behaviour associated with brands and generics and in general it is found that it is very similar.

The fact that brands do have higher prescription shares is a reflection of their current strength and also the main source of the differences in penetration and prescription frequency that exist between the two forms of drug.

For a given market share, brands and generics attract the same number of prescribers and they specify the drug with similar average frequencies. Brands attract no more loyalty as measured by the proportion of the total prescription requirements they account for, nor do they have a higher proportion and frequency of sole prescribing than do generics.

Over the whole year there was a slight partition between generic and brand prescribing for musculo-skeletal which was consistent across the three diagnoses. The pattern for cardiovasculars was even weaker and inconsistent across diagnoses. More research covering subsequent years is needed before generalisations can be made, but the current research has identified what could be termed 'weak generic proneness'.

For the manufacturer, these findings have a bearing on the decisions necessary when a drug is approaching the end of its patent protection. Assuming the market cannot be

expanded by brand development in the non-prescription sector of the market, (see Section 7.1) a manufacturer needs to decide whether to modify the brand strategy. There are essentially 4 options. Firstly, the manufacturer could reduce the price of the brand in an attempt to discourage generic competition. Secondly, the manufacturer could re-launch as a generic and cease any branding elements, and thirdly the manufacturer could retain the brand and also supply a generic version at a cheaper price. Finally, the manufacturer could continue with the status quo.

Given the expiry of patent protection, it is clear that the manufacturer's share is bound to fall with the advent of generic competition. The results in this chapter show that any strategy which assumed that doctors had strong loyalty to brands in general would probably fail and this would suggest that the first and fourth options would result in the least desirable prescription shares. The second option would probably be dysfunctional in terms of organisational motivation with representatives seeing little value in promoting the use of a 'competitive sale'.

The third option would appear to offer the best chance of defending share and in many ways is no different to the consumer goods markets where one manufacturer offers similar brands to the same customers.

For the marketer, this chapter provides some direct insights into the problems of valuing 'brand equity'. Here the conclusion is that the value of a brand can only be determined by its current and future market share. Being a 'brand' does not confer any differential advantage per se. Future market share is determined by the collective competitive actions in the market which will determine future cash flows and hence the brand's present value. In mature markets without real growth this implies a strategy of share defence.

**Appendix****Table 8A.1 'Other' Musculo-skeletal Penetration  
and Prescription Frequencies**

4 weeks	MS (%)	b(%)	w
Brufen	11.1	34	4
COPROXAMOL	10.3	37	3
IBUPROFEN	(5.6)	(14)	(4)
Ponstan	5.6	21	3
Naprosyn	5.6	24	3
CODYDRAMOL	4.7	20	3
Voltarol	4.7	22	2
Feldene	4.4	19	3
Movelat	3.5	12	3
COCODAMOL	3.4	16	2
Synflex	3.0	11	3
PARACETAMOL	3.0	19	2
Froben	2.5	11	2
Indocid	2.4	16	2
Lederfen	2.1	11	2
Surgam	1.8	9	2
Rheumox	1.8	8	3
Av. Brand	4.0	17	3
Av. GENERIC	5.4	21	3
Av. All	4.4	18	3

**Table 8A.2 Osteo-Arthritis Penetration  
and Prescription Frequencies**

12 weeks	MS (%)	b(%)	w
Indocid	8.2	13	1.3
Voltarol	8.4	12	1.5
Naprosyn	7.9	12	1.4
Oruvail	5.7	7	1.7
Brufen	5.8	9	1.3
Lodine	5.4	5	1.8
Surgam	4.8	6	1.7
Feldene	4.6	7	1.3
Lederfen	4.3	8	1.1
Froben	2.9	5	1.3
COPROXAMOL	2.6	5	1.2
PREDNISOLONE	2.5	4	1.5
Benoral	2.3	3	1.4
Rheumox	2.1	4	1.2
NAPROXEN	2.0	3	1.4
PENICILLAMINE	2.0	3	1.3
INDOMETHACIN	2.0	3	1.4
PARACETAMOL	1.5	3	1.1
IBUPROFEN	1.4	3	1.1
Av. Brand	5.2	3	1.2
Av. GENERIC	2.0	3	1.3
Av. All	4.0	3	1.2

**Table 8A.3 Hypertension Penetration and Prescription Frequencies**

12 Weeks	MS (%)	b(%)	w
Capoten	(9.0)	(18)	(4.2)
Tenormin	8.7	33	2.2
Adalat	6.9	32	1.8
Tenoretic	6.0	25	2.0
ATENOLOL	5.9	22	2.3
Cyclopen	5.8	17	2.8
BENDROFLUAZIDE	4.9	21	2.0
Innovace	4.7	18	2.2
Moduretic	4.5	18	2.1
METHYLDOPA	3.5	15	1.9
Natrilix	2.6	11	1.9
Inderal	2.6	13	1.7
Kalten	2.5	9	2.2
PROPRANOLOL	2.1	10	1.8
NIFEDIPINE	1.8	7	2.0
Av. Brand	4.9	20	2.1
Av. GENERIC	3.6	15	2.0
Av. All	4.5	18	2.1

**Table 8A.4 Angina Penetration and Prescription Frequencies**

12 Weeks	MS (%)	b(%)	w
Adalat	15.1	29	1.9
NIFEDIPINE	3.0	7	1.5
ATENOLOL	2.5	7	1.3
Tenormin	1.8	7	1.2
PROPRANOLOL	1.8	5	1.4
Inderal	1.7	5	1.2
Av. Brand	6.4	14	1.4
Av. GENERIC	2.4	6	1.4
Av. All	4.4	10	1.4

**Table 8A.5 Arrhythmia - Sole Prescribing**

4 weeks	MS (%)	bs (%)	ws	w
Digoxin	30.1	72	1.2	1.2
Inderal	21.8	78	1.3	1.3
PROPRANOLOL	11.2	71	1.1	1.1
Verapamil	9.9	56	1.2	1.3
Rythmodan	5.3	76	1.1	1.1
ATENOLOL	3.4	61	1.2	1.2
Tenormin	3.2	65	1.1	1.1
Av. Brand	5.5	69	1.2	1.2
Av. GENERIC	2.7	66	1.2	1.2
Av. All	4.5	68	1.2	1.2

**Table 8A.6 Heart Failure - Sole Prescribing**

4 Weeks	MS (%)	bs (%)	ws	w
Frumil	13.1	41	1.3	1.3
Burinex	11.7	29	1.2	1.3
FRUSEMIDE	11.5	25	1.4	1.3
Digoxin	7.5	25	1.2	1.2
Moduretic	7.2	29	1.3	1.2
Cyclopen	4.5	29	1.1	1.1
BENDROFLUAZIDE	2.6	36	1.4	1.2
Av. Brand	8.8	31	1.2	1.2
Av. GENERIC	7.1	30	1.3	1.2
Av. All	8.3	31	1.2	1.2

Table 8A.7 'Other' Cardiovasculars - Sole Prescribing

4 weeks	MS (%)	bs (%)	ws	w
Praxilene	7.4	59	1.4	1.4
Inderal	6.6	70	1.3	1.3
Digoxin	4.1	44	1.2	1.2
Trental	4.6	56	1.0	1.0
Paroven	4.1	26	1.0	1.1
PROPRANOLOL	3.6	70	1.0	1.0
Duvadilan	3.3	37	1.1	1.5
Frumil	3.3	60	1.1	1.1
Burinex	3.2	47	1.1	1.0
Persantin	3.0	53	1.0	1.0
Moduretic	2.6	49	1.1	1.1
Adalat	2.6	71	1.1	1.1
FRUSEMIDE	2.0	50	1.0	1.1
BENDROFLUAZIDE	1.6	53	1.0	1.0
ATENOLOL	1.4	78	1.0	1.0
Av. Brand	5.5	52	1.1	1.2
Av. GENERIC	2.7	59	1.0	1.0
Av. All	4.5	54	1.1	1.1

**Table 8A.8 'Other' Musculo-skeletal Penetration  
and Prescription Frequencies**

4 weeks	MS (%)	b(%)		w	
		O	T	O	T
Brufen	(11.1)	(34)	(42)	(3.6)	(2.9)
COPROXAMOL	10.3	37	40	3.1	2.8
IBUPROFEN	(5.6)	(14)	(25)	(4.4)	(2.5)
Ponstan	5.6	21	25	2.9	2.5
Naprosyn	5.6	24	25	2.6	2.5
CODYDRAMOL	4.7	20	22	2.5	2.4
Voltarol	4.7	22	22	2.4	2.4
Feldene	4.4	19	20	2.6	2.4
Movelat	3.5	12	16	3.1	2.3
COCODAMOL	3.4	16	16	2.4	2.3
Synflex	3.0	11	15	3.2	2.3
PARACETAMOL	3.0	19	15	1.7	2.3
Froben	2.5	11	12	2.5	2.3
Indocid	2.4	16	12	1.7	2.3
Lederfen	2.1	11	10	2.0	2.2
Surgam	1.8	9	9	2.3	2.2
Rheumox	1.8	8	9	2.6	2.2
Av. Brand	3.4	15	16	2.5	2.3
Av. GENERIC	5.4	23	23	2.4	2.5
Av. All	4.4	17	18	2.5	2.4
MAD Brand		2.0		0.4	
MAD GENERIC		2.2		0.3	
MAD All		2.1		0.3	
r <sup>2</sup> All		0.90			

**Table 8A.9 Osteo-Arthritis Penetration  
and Prescription Frequencies**

12 weeks	MS (%)	b(%)		w	
		O	T	O	T
Indocid	8.2	13	12	1.3	1.3
Voltarol	8.4	12	13	1.5	1.4
Naprosyn	7.9	12	12	1.4	1.3
Oruvail	5.7	7	9	1.7	1.3
Brufen	5.8	9	9	1.3	1.3
Lodine	5.4	5	7	1.8	1.3
Surgam	4.8	6	8	1.7	1.3
Feldene	4.6	7	8	1.3	1.3
Lederfen	4.3	8	7	1.1	1.3
Froben	2.9	5	5	1.3	1.2
COPROXAMOL	2.6	5	5	1.2	1.2
PREDNISOLONE	2.5	4	4	1.5	1.2
Benoral	2.3	3	4	1.4	1.2
Rheumox	2.1	4	3	1.2	1.2
NAPROXEN	2.0	3	4	1.4	1.2
PENICILLAMINE	2.0	3	3	1.3	1.2
INDOMETHACIN	2.0	3	4	1.4	1.2
PARACETAMOL	1.5	3	3	1.1	1.2
IBUPROFEN	1.4	3	2	1.1	1.2
Av. Brand	5.2	8	8	1.4	1.3
Av. GENERIC	2.0	3	3	1.3	1.2
Av. All	4.0	6	6	1.4	1.3
MAD Brand		0.8		0.2	
MAD GENERIC		0.4		0.1	
MAD All		0.7		0.2	
r <sup>2</sup> All		0.94			

**Table 8A.10 Hypertension Penetration and Prescription Frequencies**

12 weeks	MS (%)	b(%)		w	
		O	T	O	T
Capoten	9.0	18	34	4.2	2.3
Tenormin	8.7	33	33	2.2	2.2
Adalat	6.9	32	27	1.8	2.1
Tenoretic	6.0	25	24	2.0	2.1
ATENOLOL	5.9	22	23	2.3	2.1
Cyclopen	5.8	17	24	2.8	2.0
BENDROFLUAZIDE	4.9	21	20	2.0	2.0
Innovace	4.7	18	20	2.2	2.0
Moduretic	4.5	18	19	2.1	2.0
METHYLDOPA	3.5	15	15	1.9	2.0
Natrilix	2.6	11	12	1.9	1.8
Inderal	2.6	13	12	1.7	1.8
Kalten	2.5	9	11	2.2	1.8
PROPRANOLOL	2.1	10	10	1.8	1.9
NIFEDIPINE	1.8	7	8	2.0	1.8
Av. Brand	4.9	20	20	2.1	2.0
Av. GENERIC	3.6	15	15	2.0	2.0
Av. All	4.5	18	18	2.1	2.0
MAD Brand		2.1		0.2	
MAD GENERIC		0.8		0.1	
MAD All		1.6		0.2	
r <sup>2</sup> All		0.91			

**Table 8A.11 Angina Penetration and Prescription Frequencies**

12 Weeks	MS (%)	b(%)		w	
		O	T	O	T
Adalat	15.1	29	31	1.9	1.8
NIFEDIPINE	3.0	7	8	1.5	1.4
ATENOLOL	2.5	7	6	1.3	1.4
Tenormin	2.4	7	6	1.2	1.4
PROPRANOLOL	1.8	5	5	1.4	1.4
Inderal	1.7	5	4	1.2	1.4
Av. Brand	6.4	14	14	1.4	1.5
Av. GENERIC	2.4	6	6	1.4	1.5
Av. All	4.4	10	10	1.4	1.5
MAD Brand		1.3		0.2	
MAD GENERIC		0.3		0.1	
MAD All		0.8		0.1	
r <sup>2</sup> All		0.99			

**Table 8A.12 Arrhythmia - Sole Prescribing**

4 Weeks	MS (%)	bs(%)		ws	
		O	T	O	T
Digoxin	30.1	72	75	1.2	1.2
Inderal	21.8	78	73	1.2	1.2
PROPRANOLOL	11.2	71	69	1.1	1.1
Verapamil	9.9	56	69	1.2	1.1
Rythmodan	5.3	76	68	1.1	1.1
ATENOLOL	3.7	61	67	1.2	1.1
Tenormin	3.2	65	67	1.1	1.1
Av. Brand	14.1	69	70	1.2	1.1
Av. GENERIC	7.5	66	68	1.2	1.1
Av. All	12.2	68	70	1.2	1.1
MAD Brand		6.2		0	
MAD GENERIC		3.4		0	
MAD All		5.4		0	

Table 8A.13 Heart Failure - Sole Prescribing

4 Weeks	MS (%)	bs(%)		WS	
		O	T	O	T
Frumil	13.1	41	34	1.3	1.1
Burinex	11.7	29	33	1.2	1.1
FRUSEMIDE	11.5	25	33	1.4	1.1
Digoxin	7.5	25	31	1.2	1.1
Moduretic	7.2	29	31	1.3	1.1
Cyclopen	4.5	29	30	1.1	1.1
BENDROFLUAZIDE	2.6	36	29	1.4	1.1
Av. Brand	8.8	31	32	1.2	1.1
Av. GENERIC	7.1	30	31	1.3	1.1
Av. All	8.3	31	32	1.2	1.1
MAD Brand		4.1		0.1	
MAD GENERIC		7.3		0.3	
MAD All		5.0		0.2	

Table 8A.14 'Other' Cardiovasculars - Sole Prescribing

4 Weeks	MS (%)	bs(%)		WS	
		O	T	O	T
Praxilene	7.4	59	56	1.4	1.1
Inderal	6.6	70	56	1.3	1.0
Digoxin	4.1	44	55	1.2	1.0
Trental	4.6	56	55	1.0	1.0
Paroven	4.1	26	55	1.0	1.0
Propranolol	3.6	70	55	1.0	1.0
Duvadilan	3.3	37	54	1.1	1.0
Frumil	3.3	60	54	1.1	1.0
Burinex	3.2	47	54	1.1	1.0
Persantin	3.0	53	54	1.0	1.0
Moduretic	2.6	49	54	1.1	1.0
Adalat	2.6	71	54	1.1	1.0
FRUSEMIDE	2.0	50	54	1.0	1.0
Bendrofluaz.	1.6	53	53	1.0	1.0
ATENOLOL	1.4	78	53	1.0	1.0
Av. Brand	4.1	52	55	1.1	1.0
Av. GENERIC	2.2	59	54	1.0	1.0
Av. All	3.6	54	54	1.1	1.0
MAD Brand		10		0.1	
MAD GENERIC		15		0.1	
MAD All		11		0.1	

Table 8A.15 Data for Duplication Analysis in Section 8.6

	Musculo-skeletal		Cardiovascular	
	Brand	Generic	Brand	Generic
	Product Class		Product Class	
$b_{(av)}$ (%)	36	24	36	40
$w_{(av)}$	10.0	8.3	3.5	3.9
$ms_{(av)}$ (%)	1.8	1.4	2.3	2.5
No. of entities	39	20	37	6
	Other		Hypertension	
$b_{(av)}$ (%)	27	21	20	28
$w_{(av)}$	9.1	7.2	2.7	3.4
$ms_{(av)}$ (%)	1.7	1.7	2.4	3.1
No. of entities	39	19	34	6
	Rheumatoid Arthritis		Angina	
$b_{(av)}$ (%)	25	15	13	11
$w_{(av)}$	4.0	4.2	1.7	1.6
$ms_{(av)}$ (%)	2.1	1.1	3.0	1.5
No. of entities	37	19	31	5
	Osteo-arthritis		Heart Failure	
$b_{(av)}$ (%)	9	5	11	14
$w_{(av)}$	1.8	1.7	1.8	1.7
$ms_{(av)}$ (%)	2.2	1.0	3.0	3.5
No. of entities	38	18	29	4
			Arrhythmia	
$b_{(av)}$ (%)			5	5
$w_{(av)}$			1.4	1.3
$ms_{(av)}$ (%)			4.0	3.0
No. of entities			21	5
			Other	
$b_{(av)}$ (%)			4	5
$w_{(av)}$			1.4	1.3
$ms_{(av)}$ (%)			2.8	2.3
No. of entities			32	5

**Table 8A.16 Duplication Coefficients for Brands and Generics - 'Other' Musculo-skeletal Diagnoses**

48 Weeks	<u>% who also prescribe:</u>	
Prescribers of any:	Brand	Generic
Brand	1.13	1.08
Generic	1.02	1.49
Average Penetration (%)	27	21

**Table 8A.17 Duplication Coefficients for Brands and Generics - Rheumatoid Arthritis**

48 Weeks	<u>% who also prescribe:</u>	
Prescribers of any:	Brand	Generic
Brand	1.16	1.18
Generic	1.11	1.67
Average Penetration (%)	24	16

**Table 8A.18 Duplication Coefficients for Brands and Generics - Osteo-arthritis**

48 Weeks	<u>% who also prescribe:</u>	
Prescribers of any:	Brand	Generic
Brand	1.49	1.42
Generic	1.18	2.34
Average Penetration (%)	9	5

**Table 8A.19 Duplication Coefficients for Brands and Generics - Hypertension**

48 Weeks	<u>% who also prescribe:</u>	
Prescribers of any:	Brand	Generic
Brand	1.25	1.27
Generic	1.22	1.34
Average Penetration (%)	22	28

**Table 8A.20 Duplication Coefficients for Brands and Generics - Angina**

48 Weeks	<u>% who also prescribe:</u>	
Prescribers of any:	Brand	Generic
Brand	1.37	1.40
Generic	1.23	2.28
Average Penetration (%)	14	11

**Table 8A.21 Duplication Coefficients for Brands and Generics - Heart Failure**

48 Weeks	<u>% who also prescribe:</u>	
Prescribers of any:	Brand	Generic
Brand	1.52	1.32
Generic	1.49	1.39
Average Penetration (%)	12	14

**Table 8A.22 Duplication Coefficients for Brands and Generics - Arrythmia**

48 Weeks	<u>% who also prescribe:</u>	
Prescribers of any:	Brand	Generic
Brand	1.79	1.50
Generic	1.51	1.66
Average Penetration (%)	6	5

**Table 8A.23 Duplication Coefficients for Brands and Generics - 'Other' Cardiovasculars**

48 Weeks	<u>% who also prescribe:</u>	
Prescribers of any:	Brand	Generic
Brand	1.96	1.72
Generic	1.76	1.78
Average Penetration (%)	5	5

**Table 8A.24 Prescribing of Individual Brands and their Generic Equivalents - 'Other' Musculo-skeletal**

12 weeks	MS (%)	b(%)		w		wp	
		O	T	O	T	O	T
Brufen	11.1	52	61	7.1	6.0	38	40
IBUPROFEN	5.6	19	39	4.4	2.5	38	42
Naprosyn	5.6	40	39	2.6	2.5	40	42
NAPROXEN	1.3	9	11	2.5	2.4	37	44
Voltarol	4.7	35	34	2.4	2.4	39	42
Diclofenac	0.6	1	1	2.5	2.4	38	45
Indocid	2.4	32	20	1.7	2.3	41	44
INDOMETHACIN	1.7	15	14	2.5	2.4	39	44
Feldene	4.4	33	32	2.6	2.4	39	43
Piroxicam	0.2	3	2	2.4	2.3	40	45
Lederfen	2.1	21	17	3.1	2.3	41	44
Fenbufen		2	1	2.4	2.3	48	45
Froben	2.5	20	20	3.2	2.3	43	43
Flurbiprofen		1	1	1.7	2.3	30	45

**Table 8A.25 Prescribing of Individual Brands and their Generic Equivalents - Osteo-arthritis**

12 weeks	MS (%)	b(%)		w		wp	
		O	T	O	T	O	T
Brufen	5.4	9	9	1.3	1.3	5	5
IBUPROFEN	1.4	3	2	1.1	1.2	3	5
Naprosyn	7.9	12	12	1.4	1.3	4	5
NAPROXEN	2.0	3	4	1.4	1.2	4	5
Voltarol	8.3	12	13	1.5	1.3	5	5
Diclofenac	0.8	1	1	1.4	1.2	7	5
Indocid	7.8	13	13	1.3	1.3	4	5
INDOMETHACIN	2.0	3	3	1.4	1.2	5	5
Feldene	4.6	7	8	1.3	1.3	5	5
Piroxicam	0.6	1	1	1.0	1.2	4	5
Lederfen	4.1	8	7	1.1	1.2	4	5
Fenbufen	0.2	.4	.4	1.0	1.1	3	5
Froben	2.8	5	5	1.3	1.2	4	5
Flurbiprofen		.4	2	5.0	1.2	8	5

**Table 8A.26 Prescribing of Individual Brands and their Generic Equivalents - Angina**

12 weeks	MS (%)	b(%)		w		wp	
		O	T	O	T	O	T
Tenormin	2.4	7	6	1.2	1.4	7	7
ATENOLOL	2.5	7	6	1.3	1.4	7	7
Adalat	15.1	29	31	1.9	1.8	6	6
NIFEDIPINE	3.0	7	8	1.5	1.4	6	7
Inderal	1.7	5	4	1.2	1.4	7	7
PROPRANOLOL	1.8	5	5	1.4	1.4	7	7

**Table 8A.27 Prescribing of Individual Brands and their Generic Equivalents - Heart Failure**

12 weeks	MS (%)	b(%)		w		wp	
		O	T	O	T	O	T
Frumil	13.1	19	20	1.8	1.7	5	6
FRUSEMIDE	11.5	17	18	1.7	1.6	6	6

**Table 8A.28 Prescribing of Individual Brands and their Generic Equivalents - Arrhythmia**

12 weeks	MS (%)	b(%)		w		wp	
		O	T	O	T	O	T
Tenormin	3.2	2	2	1.2	1.4	3	3
ATENOLOL	3.7	2	2	1.4	1.4	3	3
Inderal	21.8	10	12	1.5	1.4	3	3
PROPRANOLOL	11.2	6	6	1.5	1.4	3	3

**CHAPTER 9: CAPOTEN - AN EXCEPTION TO THE RULE****Summary****9.1 Introduction****9.2 Deviations from Dirichlet Norms in a Year****9.3 Deviations from Dirichlet Norms by Quarter****9.4 The Capoten Post-Marketing Study****9.5 Comments on the Capoten Post-Marketing Study****9.6 Conclusions**

### Summary

Capoten was prescribed differently to other anti-hypertensives during 1986. The post-marketing study activities carried out by the brand's manufacturer during that year could account for the differences in the prescribing behaviour associated with Capoten.

The post-marketing study made free computing equipment available to certain prescribers and thus had the effect of making Capoten very different to the other available drugs. This difference had an effect which appears to have been temporary.

Despite the noticeable difference in prescribing behaviour, Capoten remained similar in many ways to the other drugs in the diagnosis. The effect of the post-marketing study was significant but quite small.

Dirichlet modelling could be used as part of the monitoring and control of pharmaceutical prescribing.

### 9.1 Introduction

In Chapters 4,6,7 and 8, one brand has stood out as different from the others. Capoten is prescribed in a way which is not predicted by Dirichlet theory and this chapter aims to help in understanding how and why it is different.

**Section 9.1** tabulates various prescribing behaviour measures for Capoten and compares them with the Dirichlet predictions for a brand with comparable market share. It also compares Capoten to another similar brand which is closely modelled by the Dirichlet.

**Section 9.2** analyses Capoten by quarter and shows that the deviations decrease through the year and how the deviations are due to a shortage of infrequent prescribers and a surfeit of 'heavy' users.

**Section 9.3** describes the key market place activities directed at Capoten during 1986 and these help explain the differences between Capoten and the other anti-hypertensives. **Section 9.4** provides some comments on the activities during the year and the chapter ends with a conclusion.

### 9.2 Deviations from Dirichlet Norms in a Year

A total of 751 prescriptions were written for Capoten during the year of which 736 were for the hypertension diagnosis. The analysis can therefore safely exclude the other diagnoses. For the year as a whole, table 9.1 shows the observed and Dirichlet predictions for a variety of prescribing behaviour measures.

**Table 9.1 Capoten - Prescribing Behaviour**

Hypertension (48 weeks)	O*	T*
Penetration (b) (%)	31	58
Average Prescription Frequency (w)	10	5
Rate of Hypertension Prescribing (wp)	50	44
Share of Requirements (w/wp) (%)	20	12
Sole Prescribers (month) (bs) (%)	13	12
Sole Prescribing rate (month) (ws)	1.6	1.2
Percentage writing 9+ prescriptions (h) (%)	33	17

\* O = Observed, T = Dirichlet Predictions

In the year, Capoten was prescribed by about 30% of doctors as opposed to the 60% predicted by the Dirichlet. As a consequence the observed average prescription frequency was twice the theoretical figure of 5 times in the year.

Prescribers of Capoten wrote an average of 50 prescriptions for hypertension, 6 more than predicted by the Dirichlet. This means that Capoten accounted for 20% of its prescribers' needs versus the 12% predicted by the Dirichlet. Even for this case where a brand has twice the predicted prescription frequency it is worth noting that on average, doctors use other entities to satisfy 80% of their hypertension prescribing needs. In this sense, Capoten is

more similar to other anti-hypertensives than it is different.

The incidence of sole prescribing and the associated prescription frequency was close to the Dirichlet predictions.

The main source of the deviation is found in the number of doctors who prescribed Capoten frequently in the year. It is observed that 33% of the 76 doctors prescribed nine times or more versus the 17% predicted by the Dirichlet. This surfeit equates to 12 doctors or 5% of the sample. The distribution of prescription frequencies is shown in more detail in table 9.2.

**Table 9.2 Capoten - Distribution of Prescribing**

48 Weeks		<u>% of Doctors Prescribing 1-4, 5-8 .... Times</u>					
		1-4	5-8	9-12	13-16	17-20	21+
Capoten	O	55	12	8	4	5	16
	T	66	18	8	4	2	2

\* O = Observed, T = Dirichlet Predictions

This shows that there is a surfeit of very heavy prescribers at above 16 times in a year and a shortfall of light prescribers prescribing eight times or less in a year. For doctors who prescribe at between 9 and 16 times in the year, the model predicts the observed frequencies very well.

As a summary, it is useful to compare Capoten to Innovace, the only other drug with the same mode of operation (known as ACE inhibition) and which is therefore the most similar anti-hypertensive (see Section 9.4).

Here a very similar drug is modelled closely by the Dirichlet. It might be argued that some prescribing of Capoten was at the expense of Innovace. If this were true, then one would expect to see low duplications of prescription between these two drugs. On average, however,

41% of the prescribers of any drug also prescribed Innovace in the year, and 42% of Capoten prescribers also used Innovace in 1986.

**Table 9.5 Prescribing of Capoten and Innovace**

Hypertension (48 weeks)				
	Capoten		Innovace	
	O	T	O	T
b (%)	31	58	36	37
w	10	5	4	4
wp	50	44	43	47
w/wp (%)	20	12	10	9
(bs) month(%)	13	12	13	11
(ws) month	1.6	1.2	1.3	1.2
9+ scripts(%)	33	17	11	13

\* O = Observed, T = Dirichlet Predictions

### 9.3 Deviations from Dirichlet Norms by Quarter

In order to see whether the deviations from the Dirichlet were consistent, the model was run separately on all four quarters of the year. Table 9.3 shows prescribing behaviour measures for the four quarters separately and also the Dirichlet predictions for a brand with Capoten's share. It shows that the deviations are highest in the first quarter and then decline over the second and third quarters with little difference between the third and fourth quarters.

**Table 9.3 Capoten - Prescribing Behaviour by Quarter**

Hypertension (4 quarters)					
	Q1	Q2	Q3	Q4	Q
	O	O	O	O	T
b (%)	16	20	17	19	34
w	5.2	4.6	3.5	3.6	2.2
wp	17	16	13	17	14
w/wp (%)	30	29	16	21	17
(bs) month(%)	13	17	12	9	12
(ws) month	2.1	1.9	1.2	1.0	1.2
9+ scripts(%)	26	19	5	5	2

\* O = Observed, T = Dirichlet Predictions

The picture can be seen in detail by comparing the distribution of prescription frequencies for the first and fourth quarters along with the Dirichlet prediction. This is shown in table 9.4.

**Table 9.4 Capoten - Distribution of Prescribing by Quarter**

	<u>Number of doctors</u> <u>prescribing 1,2,3.....n times</u>					
	1	2	3	4	5	6+
Quarter 1	5	1	2	1	1	5
Quarter 4	6	3	3	2	1	2
Dirichlet	18	7	4	2	1	1

It can be seen that in quarters 1 and 2 there is a shortfall of doctors prescribing Capoten once or twice, and for quarter 1 a surfeit of frequent prescribers. By quarter 4 there is still a shortfall of light prescribers (although a smaller shortfall than quarter 1) and the surfeit of frequent prescribers is only one doctor.

In order to examine the heavy prescribers in detail, the top 9 were identified in each quarter and ranked. This resulted in a total of 17 doctors, only two of whom prescribed Capoten in all four quarters. Of the rest, five prescribed in three quarters, three prescribed in two quarters and seven prescribed in one quarter only.

Of the 17 heavy prescribers, 14 were male, 10 were young and only two were dispensing doctors. These figures are very close to the overall representation in the panel. Only about half of the heavy prescribers described themselves as of British origin compared to 75% of the panel.

This section shows that Capoten was prescribed differently to the other anti-hypertensives in 1986. There is evidence of higher than expected prescription frequency and non-stationary behaviour. Even though the differences can be traced to a small number of doctors, they show up as a consistent deviation from Dirichlet norms, and this

demonstrates that the model can be a very sensitive benchmark for evaluating prescribing behaviour. It also directs attention to where to look for the reasons for the differences.

The following section describes the main activities surrounding Capoten in 1986.

#### **9.4 The Capoten Post-Marketing Study**

The manufacturer of Capoten instigated a study in July 1983 which lasted until November 1987. During this period 2000 General Practitioners prescribed Capoten to a total of 60,000 patients (Squibb, 1988). The major thrust of the study which had been sanctioned by the ethics committee of the British Medical Association occurred during 1986 when the data for the current research was collected.

The study had five key elements (Piercy, 1990):

1. G.Ps. were to be asked to prescribe Capoten and then report back information to the company on various aspects of the patients' health during subsequent months.
2. A BBC personal computer was allocated to each participating doctor so that results could be transmitted to the manufacturer via the British Telecom Viewdata network without the need for written reports. The computers were formally loaned to the participating doctor, but it was made clear that the company would be highly unlikely to reclaim them.

If a doctor did not have a modern telephone connection socket, Squibb paid for its installation, but the rental and usage cost of the line (which was normally domestic) was the responsibility of the doctor. This means that the only costs incurred by the doctor were those of the costs of the telephone calls to Squibb to transmit the patient data.

3. Each potential G.P. participant was informed that at a commitment to put at least 10 patients on Capoten would be needed prior to inclusion in the study and the installation of equipment. There was also a scale of further incentives such as computer printers and other peripherals available to study participants who exceeded the minimum target of 10 patients.

4. Each participant received a quarterly update on the progress of the study and was also invited to local and national meetings.

5. Each Squibb representative had a target of about 20 G.Ps. to recruit into the study.

One question that arises is whether this activity was on the one hand a pure research exercise or on the other merely a sophisticated promotional marketing programme designed solely to increase sales of Capoten. Given its sanction from the medical profession it might be hard to conclude that the latter was true, but there is additional evidence to support the proposition of a marketing led operation.

In 1985 a competing brand called Innovace was launched with a recommendation for prescribing in a wider hypertension context than Capoten. In addition, because it was a new drug, Merck, Sharpe and Dhorne were able to justify a larger advertising and promotional spend than Capoten in keeping with the government guide-lines (see Chapter 2). In practice, Piercy (1990) estimated that Innovace benefited from a 35% higher marketing spend than Capoten during 1986. As Capoten was an older brand, Squibb was restricted in terms of the expenditure allowed. Given the constraints and the anticipated promotional disadvantage it is reasonable to see the post-marketing programme as one way of recovering the lost ground.

According to the study report some 2000 doctors were recruited, representing about 6% of the G.P. population (see Chapter 2). As the panel is closely representative of the population, a similar proportion should have been recruited to the study representing about 13 doctors. Table 9.1 showed that 33% of prescribers were heavy prescribers versus the 17% predicted by the Dirichlet. During the year, a total of 76 doctors prescribed Capoten and therefore the surfeit of heavy prescribers is about 12 doctors. By the end of the year as the post-marketing study was winding down, the surfeit of heavy prescribers had already decreased to one doctor.

In operating the programme, Squibb were clearly targeting a relatively small number of doctors who would then become relatively frequent prescribers - a segmented approach. There is anecdotal evidence (Piercy 1990) that they targeted doctors with a non-British origin and this is not refuted by the data in the current research (see Section 9.3). In terms of outcome, the company succeeded in achieving a share about twice as high as the number of prescribers would suggest.

The conclusion is that the result of the post-marketing study was to provide a medium term promotional effect which diminished as the study ended. It would be interesting to analyse data for subsequent years to see whether any long term benefits from the study accrued to the brand.

#### **9.5 Comments on the Capoten Post-Marketing Study**

In his 1990 study, Piercy interviewed 10 G.Ps., none of whom had been part of the Capoten study but all of whom knew about it. When asked their opinions about it, some felt that Squibb had shown favouritism to a few doctors while others saw it as just another way to try and increase sales. Three of the interviewees felt that it was unethical to actually give away computers and that the study amounted to nothing more than an overt bribe in return for prescriptions.

This perception of bribery is widespread both among doctors and outside the industry. Graves (1987) directly criticises Ayerst Laboratories for operating a frequent flyer incentive in the USA based on the number of prescriptions a doctor wrote for Inderal LA. When a doctor had prescribed the brand for 50 patients and completed a seven question survey, they would receive an airline ticket to any destination in the USA. There were escalating rewards up to a maximum of 200 patients for whom the doctor prescribed the drug.

Wall (1987), citing a working party of the Royal College of Physicians describes how some doctors demand substantial gifts or cash payments for seeing representatives or starting patients on a new drug.

Thompson (1988) cites the offer of a free transatlantic trip to hear a presentation on a new drug and asks whether he is

'...to repay the firm by helping it market the drug?  
Therein lies the conflict of interest' p. 835

Sims and Durie (1987) quote a doctor who recalled being targeted by representatives with incentives early in his career before his prescribing habits became established.

In a wider context, Clark (1988) cites incentives ranging from the provision of free meals to the permanent 'loan' of photocopying machines as contributing to the danger of doctors losing public confidence. Erlichman (1988) refers directly to the Capoten post-marketing study as an example of companies appearing caring and vigilant when they ask doctors to monitor patients on specific drugs. In reality (according to Erlichman) the real aim is often to use the trial as a concealed means of grabbing market share from rival brands. In the case of Capoten, Erlichman claims that the study failed to detect the tendency for the drug to cause kidney damage in some patients.

### 9.6 Conclusions

There is no doubt that the Capoten post-marketing study of 1986 succeeded in achieving a higher level of sales than would have otherwise occurred. It is not possible to evaluate the desirability of the study in the context of the current research, but certain conclusions may be drawn.

If the study is viewed as a highly focussed 'promotion', then there is evidence that the effect was temporary and that once it ceased, prescribing behaviour started to reflect Dirichlet norms. Pre and post 1986 data would be required to check this tentative conclusion.

Even in this case, where one brand was presented as substantively different from the others (by virtue of the free computing equipment available only to its users!), its prescribers used other drugs five times more frequently than Capoten. If the offer of added value on this scale increases 'loyalty' by such a small amount, then marketers should have low (if any) expectations of promotions in consumer markets.

While it seems likely that there was a main competitive target, there is no evidence that the post-marketing study affected the prescribing behaviour associated with Innovace, which was in line with Dirichlet predictions for its market share. Without the Capoten activity, there remains the possibility that Innovace would have achieved higher sales.

The analysis of Capoten's market performance in terms of penetration and average prescription frequency and the additional use of the Dirichlet showed how this particular brand differed from the others. In this market where there is a high degree of political and public interest and concern about resource allocation and utilisation, this form of analysis could be routinely used as part of a monitoring and control purpose to ensure that any exceptional brands were investigated (See Chapter 12).

**CHAPTER 10: PRESCRIBING ACROSS THE TWO PRODUCT CLASSES AND  
THE ROLE OF THE FAVOURITE BRAND**

**Summary**

**10.1 Introduction**

**10.2 Penetrations and Prescriptions Frequencies  
Across Two Product Fields**

**10.3 Total Prescribing and Share of Requirements  
Across Two Product Fields**

**10.4 Sole Prescribing Across Two Product Fields**

**10.5 Duplications Across Two Product Fields**

**10.6 The Importance of the Favourite Brand**

**10.7 A Simplified Loyalty Based Comparison**

**10.8 Conclusions**

### Summary

Once the overall rates of prescribing are taken into account, there are no significant differences in the way that drugs are prescribed in different product classes. The dominant determinant of prescribing behaviour remains a drug's market share, irrespective of the type of drug.

The generic partition identified in **Chapter 8** persists for prescribers across the two product classes. A doctor who prescribes a cardiovascular generic is more likely to also prescribe a generic for Rheumatoid Arthritis than is a prescriber of a brand for Rheumatoid Arthritis.

The role of the favourite brand in the portfolio is examined and it is found that its share varies with the total number of brands used. In addition the favourite brand's share seems to account for a slightly higher proportion of the doctor's total needs than expected from a pure zero order process.

### 10.1 Introduction

In this chapter the two product fields are combined in a natural experiment to see how the same doctors prescribe drugs for very different conditions. Little prior research has explored this aspect of buyer behaviour and where it has been examined, further research was suggested as conclusions were tentative. Ellis (1989) found a small market segment effect which was termed 'private label prone' in that consumers of private label fruit squash were more likely than the average consumer to also purchase private label fabric conditioner. The segment was not identifiable from demographic analysis and is therefore similar to the diagnosis partitions (**Chapter 7**) and the generic partitions (**Chapter 8**) of the current research.

The analysis of prescribing across two very different conditions is an extension to existing knowledge of buying

behaviour and also provides some new knowledge about the prescribing of generics and brands across product classes.

Combining product fields which have very different overall rates of prescribing presents a problem which can be solved by using a subset of one product field in order to equalise the prescribing rates. In essence there are two ways of proceeding. Firstly, different time periods could be utilised, but this would present problems in analysing other time periods. Secondly, a portion of one data set which matches the other in size can be extracted and this means that the rates of prescribing are consistent through time.

Table 2.4 shows that the total number of prescribing doctors and prescriptions are very similar for the cardiovascular product field and the Rheumatoid Arthritis diagnosis of the musculo-skeletal product field. The difference is summarised by comparing the average total annual prescribing rates for the two data sets which are 62 for Rheumatoid Arthritis and 64 for all cardiovasculars.

The analyses conducted in this chapter were carried out on these two data sets which were aggregated. A selection of the largest brands and generics from each set were identified and used in the analysis.

**Section 10.2** summarises the penetration and prescription frequency for these 14 drugs and describes the fit with the Dirichlet. **Section 10.3** repeats the analysis for total prescribing and the individual drug's share of the doctors' requirements. **Section 10.4** looks at sole prescribing.

In **Section 10.5** duplications of prescribing between cardiovascular and Rheumatoid Arthritis are analysed in order to examine any partitioning that exists.

**Section 10.6** examines the role of the favourite brand in doctors' prescribing and **Section 10.7** compares the observed

favourite brand shares with the two extremes of 'loyalty' and 'disloyalty'. The chapter concludes with a summary.

### 10.2 Penetrations and Prescription Frequencies across Two Product Fields

Table 10.1 lists the observed and Dirichlet predictions of penetrations and prescription frequencies for selected brand and generic entities. Together they account for around 40% of the total number of prescriptions written for cardiovasculars and Rheumatoid Arthritis. The table is organised by the four categories of drug in the analysis and this is consistent with decreasing market share order with a few exceptions.

The table shows the downward Double Jeopardy pattern with high penetrations and prescription frequencies accompanying larger market shares. The averages towards the foot of the table show that the key difference between any form of the data is represented by market share. Without prior labelling of the drugs in table 10.1 it would be impossible to identify the product class from which it came.

The table also provides the Dirichlet predictions for the combined Cardiovascular/ Rheumatoid Arthritis market and the excellent degree of fit is summarised by the r-squared coefficient between the observed and predicted penetrations (0.92). The mean absolute deviations between the observed and Dirichlet predictions were also calculated and found to be 3.5% for penetration and 0.3 for average prescription frequency. These calculations also confirm the fit of the Dirichlet.

This shows that once the 'product class specific' rate of prescribing has been accounted for there is little if any difference between the way that drugs are prescribed in terms of their penetration and prescription frequency.

**Table 10.1 Observed and Theoretical Penetrations and Prescription Frequencies Across Two Product Fields**

12 weeks	MS (%)	b(O) (%)	b(T) (%)	w(O)	w(T) <sup>-</sup>
Brufen Mb <sup>+</sup>	5.6	50	53	3.6	3.3
Voltarol Mb	4.3	43	44	3.2	3.1
Naprosyn Mb	4.1	41	43	3.2	3.0
Feldene Mb	3.2	35	36	2.9	2.8
Adalat Cb	3.6	49	39	2.4	2.9
Tenormin Cb	2.7	37	31	2.3	2.7
Cyclopenthiazide Cb	2.0	22	24	2.8	2.6
Coproxamol Mg	2.4	32	28	2.4	2.7
Paracetamol Mg	1.4	23	17	1.9	2.4
Codydramol Mg	1.1	16	14	2.1	2.4
Atenolol Cg	1.9	26	24	2.4	2.6
Bendrofluazide Cg	1.6	24	20	2.2	2.5
Propranolol Cg	1.1	18	15	2.0	2.4
Frusamide Cg	1.1	20	14	1.7	2.4
Av Musc. (brand)	4.3	42	44	3.2	3.1
Av Card. (brand)	2.7	32	31	2.9	2.7
Av Musc. (generic)	1.7	22	20	2.5	2.5
Av Card. (generic)	1.4	22	18	2.1	2.5
Av Musc.	3.0	34	34	2.8	2.8
Av Card.	2.1	28	24	2.3	2.6
Av brand	3.5	37	37	3.1	2.9
Av generic	1.6	22	19	2.3	2.5
Av all	2.5	29	28	2.7	2.7
r-sq		0.92			

**Note:** <sup>+</sup> M is a Rheumatoid Arthritis Entity, C is a cardiovascular, b is a brand and g is a generic.  
O = Observed, T = Dirichlet Prediction.

### 10.3 Total Prescribing and Share of Requirements across Two Product Fields

There is no intrinsic reason to expect that the way in which doctors spread their prescribing requirements across the available drugs for heart diseases and Rheumatoid Arthritis should be similar. The results in Section 10.2, however, showed that the Dirichlet modelled prescribing behaviour

across the two product fields well, using (essentially) only market shares as inputs. From this it would be predicted that drugs with similar market shares would also have similar total rates of prescription and that they would account for similar proportions of their prescribers total needs. Table 10.2 shows the data which confirms this deduction.

Overall, the prescribers of any drug write an average of about 40 prescriptions for the product field and the averages towards the foot of table 10.2 show little variation from this figure. Indeed the product class prescribing rate varies little across all 16 drugs in the table, with perhaps drugs of higher market share exhibiting slightly lower product class prescribing rates than small share drugs. This 'Natural Monopoly' finding is consistent with the empirical patterns in Chapters 6 & 7, and prior research (Ehrenberg, 1988). The correlation between the observed and predicted total prescribing rate is 0.88 which is remarkably high given the small range of the observed and predicted data.

A slightly different pattern is found for a drug's share of total requirements due to the Double Jeopardy pattern and the differences in average prescription frequencies. Thus Brufen at the top of the table accounts for 10% of its doctors' needs whereas Frusamide (at the foot of the table) accounts for just 4% of its doctors' needs. Again, this pattern is familiar and shows that loyalty is not increased through appealing to a smaller number of doctors.

The theoretical predictions in table 10.2 again fit the observed data well with the mean absolute deviations between the share of requirements of 1% and a correlation of 0.94.

**Table 10.2 Observed and Theoretical Total Prescribing Rates and Share of Requirements Across Two Product Fields**

12 Weeks		MS (%)	wp (O)	wp (T)	Share of Requirements (O%) (T%)	
Brufen	Mb <sup>+</sup>	5.6	37	39	10	9
Voltarol	Mb	4.3	37	39	9	8
Naprosyn	Mb	4.1	38	39	8	8
Feldene	Mb	3.2	39	40	7	7
Adalat	Cb	3.6	39	40	6	7
Tenormin	Cb	2.7	41	40	6	7
Cyclopenthiazide	Cb	2.0	45	41	6	6
Coproxamol	Mg	2.4	43	40	6	7
Paracetamol	Mg	1.4	44	41	4	6
Codydramol	Mg	1.1	45	41	5	6
Atenolol	Cg	1.9	40	41	6	6
Bendrofluazide	Cg	1.6	42	41	5	6
Propranolol	Cg	1.1	42	41	5	6
Frusamide	Cg	1.1	43	41	4	6
Av Musc. (brand)		4.3	38	39	9	8
Av Card. (brand)		2.7	42	40	6	7
Av Musc. (generic)		1.7	42	41	5	6
Av Card. (generic)		1.4	42	41	5	6
Av Musc.		3.0	40	41	7	7
Av Card.		2.1	42	41	5	6
Av brand		3.5	40	40	7	7
Av generic		1.6	42	41	5	6
Av all		2.5	41	40	6	7

**Note:**<sup>+</sup> M is a Rheumatoid Arthritis Entity, C is a cardiovascular, b is a brand and g is a generic. O = Observed, T = Dirichlet Prediction.

#### **10.4 Sole Prescribing across Two Product Fields**

Just as there was no prior reason to expect doctors to spread their requirements in a similar way across two product classes, neither is there any reason to expect drugs in different product fields to attract similar levels and rates of sole prescribing. Using the results of the previous two sections, however, would lead again to the prediction that they would indeed turn out to be similar and well

modelled by the Dirichlet, and table 10.3 shows this to be the case. Because the rates of sole prescribing are so low, the data in table 10.3 are based on an average month in order to see the patterns clearly.

**Table 10.3 Observed and Theoretical Sole Prescribing Rates**

4 weeks	MS (%)	bs (O%)	bs (T%)	ws (O)	ws (T)
Brufen Mb <sup>+</sup>	5.6	1.8	1.1	1.5	1.2
Voltarol Mb	4.3	1.7	1.0	1.0	1.2
Naprosyn Mb	4.1	1.6	1.0	1.8	1.2
Feldene Mb	3.2	1.1	1.0	1.0	1.2
Adalat Cb	3.6	1.1	1.0	1.4	1.2
Tenormin Cb	2.7	0.4	0.9	1.0	1.2
Cyclopenthiazide Cb	2.0	0.3	0.9	1.0	1.1
Coproxamol Mg	2.4	0.2	0.9	1.0	1.1
Paracetamol Mg	1.4	-	0.9		
Codydramol Mg	1.1	-	0.8		
Atenolol Cg	1.9	1.1	0.9	1.5	1.1
Bendrofluazide Cg	1.6	0.7	0.9	1.0	1.1
Propranolol Cg	1.1	0.7	0.8	1.0	1.1
Frusamide Cg	1.1	1.1	0.0	1.0	1.1
Av Musc. (brand)	4.3	1.6	1.0	1.3	1.2
Av Card. (brand)	2.7	0.6	1.0	1.1	1.2
Av Musc. (generic)	1.7	0.1	0.9	1.1	1.1
Av Card. (generic)	1.4	0.9	0.9	1.1	1.1
Av Musc.	3.0	0.9	1.0	1.3	1.2
Av Card.	2.1	0.8	0.9	1.1	1.1
Av brand	3.5	1.1	1.0	1.2	1.2
Av generic	1.6	0.5	0.9	1.1	1.1
Av all	2.5	0.8	0.9	1.2	1.1

**Note:**<sup>+</sup> M is a Rheumatoid Arthritis Entity, C is a cardiovascular, b is a brand and g is a generic. Paracetamol and Codydramol had no sole prescribers in any of the 12 months.

O = Observed, T = Dirichlet Prediction.

The fit for the proportion of sole prescribers as measured by correlation is worse than the previous examples at 0.67. The reason here is that the actual and predicted incidence of sole prescribing is so low in any case. The model

predicts that one of each drug's prescribers will be a sole prescriber in a month and the actual numbers were either 0 or one for the product class.

### 10.5 Duplications Across Two Product Fields

Chapter 8 demonstrated that there was a market partition in both cardiovasculars and musculo-skeletal and that prescribers of one generic drug were more likely to prescribe other generic drugs than the population as a whole. Here the analysis is extended to see whether doctors who prescribe generics for Rheumatoid Arthritis are more likely to prescribe generics for cardiovasculars than are prescribers of brands for cardiovasculars.

Table 10.4 reproduces the duplications for 16 of the drugs prescribed. The table is organised in order to show the sixteen different parts of the body of the table which are further summarised in table 10.5 below.

The duplication coefficient of 1.15 indicates the overall degree of flatness in the data. However, by calculating separate coefficients for each section of the data, table 10.5 does clarify that the generic partition generalises to prescribing across both product fields.

Table 10.5 shows that on average, a cardiovascular generic will be prescribed by a higher proportion of the prescribers of a Rheumatoid Arthritis generic prescriber when compared to prescribers of either cardiovascular or Rheumatoid Arthritis brands. However, because these latter drugs have higher shares and penetrations, the absolute duplications will still be higher.

Nevertheless, the analysis does provide evidence of a general but small generic proneness in the prescribing of pharmaceuticals.

**Table 10.4 Duplication of Prescribing  
Across Two Product Fields**

12 weeks Prescrib- -ers of:	Duplicate Prescribers Table (O)															
	<u>%Who also prescribe</u>															
	Br	Vo	Na	Fe	Ad	Te	Ca	Na	Co	Ib	Pa	Co	At	Be	Pr	Fr
Brufen		46	46	38	55	43	17	27	41	10	26	22	25	23	14	20
Voltar	54		41	39	56	44	22	24	35	14	22	17	26	26	18	19
Napros	56	44		41	53	41	20	22	36	14	26	18	26	25	16	19
Felden	54	48	47		57	43	20	25	37	15	28	20	29	24	19	23
Adalat	57	50	44	41		50	26	25	38	14	27	20	27	28	17	23
Tenorm	58	51	45	41	65		24	28	37	11	29	21	20	26	16	25
Capote	47	51	43	38	67	48		27	38	16	27	18	27	35	19	25
Cyclop	61	45	40	38	54	47	22		45	18	27	25	32	33	26	27
Coprox	63	47	46	41	57	43	22	31		18	33	27	30	30	21	26
Ibupro	31	39	37	32	44	25	19	26	36		30	18	43	43	28	33
Parace	56	42	46	43	58	47	22	27	47	21		25	35	34	23	28
Codydr	66	45	46	44	60	49	20	35	54	17	35		29	34	20	26
Atenol	48	44	41	39	52	29	20	28	37	27	31	19		41	27	32
Bendro	49	48	42	36	57	41	28	31	41	28	33	23	45		32	34
Propra	39	44	37	37	47	34	21	34	38	25	30	19	40	44		32
Frusam	49	40	38	40	55	47	23	31	42	26	32	21	41	40	28	
Av Mb	55	46	45	39	55	43	20	24	37	13	25	19	26	24	16	20
Av Cb	55	49	43	39	62	48	24	27	39	15	27	21	27	30	20	25
Av Mg	54	43	44	40	55	41	21	30	45	19	33	23	34	35	23	28
Av Cg	46	44	39	38	53	38	23	31	39	27	31	20	42	42	29	33
Av All	52	46	43	39	56	42	22	28	40	18	29	21	32	32	22	26
Pen	50	43	41	35	49	37	19	22	32	16	23	16	26	24	18	20
D=	1.15															

**Table 10.5 Duplication Coefficients of Prescribing  
Across Two Product Fields**

12 Weeks	RAb	Cb	RAg	Cg
Rheumatoid-Arthritis (brand)	1.10	1.13	1.10	1.01
Cardiovascular (brand)	1.11	1.27	1.18	1.18
Rheumatoid-Arthritis (generic)	1.08	1.15	1.38	1.39
Cardiovascular (generic)	1.00	1.14	1.36	1.68
Average Penetration (%)	42	32	22	22

### 10.6 The Importance of the Favourite Brand

The second area of study in this chapter is an examination of the importance of the favourite brand in the doctor's portfolio or 'consideration set'. If prescribing is dominated by one brand, then the marketing task is not only to assist entry into the consideration set but also to develop it into the favourite brand. If, on the other hand doctors spread their prescriptions equally among the set members, then the task is to gain entry and then stay in the set.

**Table 10.6 The Share of the Favourite Brand**

	Total no of Scripts (Average)	Average no of Brands	Average share of Favourite Brand
M1y	132	15	39
M2y	62	12	33
C1y	34	9	36
M1q	36	8	43
M2q	15	6	42
C1q	10	5	51
C3y	12	5	49
C2y	15	5	47
M3y	9	5	45
C4y	5	3	67
C2q	5	3	64
C3q	4	3	58
C5y	5	2	73
M3q	3	2	66
C4q	2	2	86
C5q	2	2	80

**Key:** M1-M3 are the three Musculo-skeletal diagnoses  
C1-C5 are the five Cardiovascular diagnoses  
y=year and q=quarter

Table 10.6 shows a clear relationship between the number of brands in the consideration set and the share of prescriptions accounted for by the favourite brand. As the number of brands increases the average share of the favourite declines from 80% to around 30% which appears to be a base figure when the mean consideration set size is

greater than 6 brands. The interesting question to answer is how these shares reflect the degree of loyalty to brands in the consideration set.

### 10.7 A Simplified Loyalty Based Comparison

The two possible extremes of the share of prescriptions accounted for by the favourite brand can be described by

$Y = 100 - \{(X-1)100/T\}$  when the prescribing behaviour is as close possible to a 'loyal' model

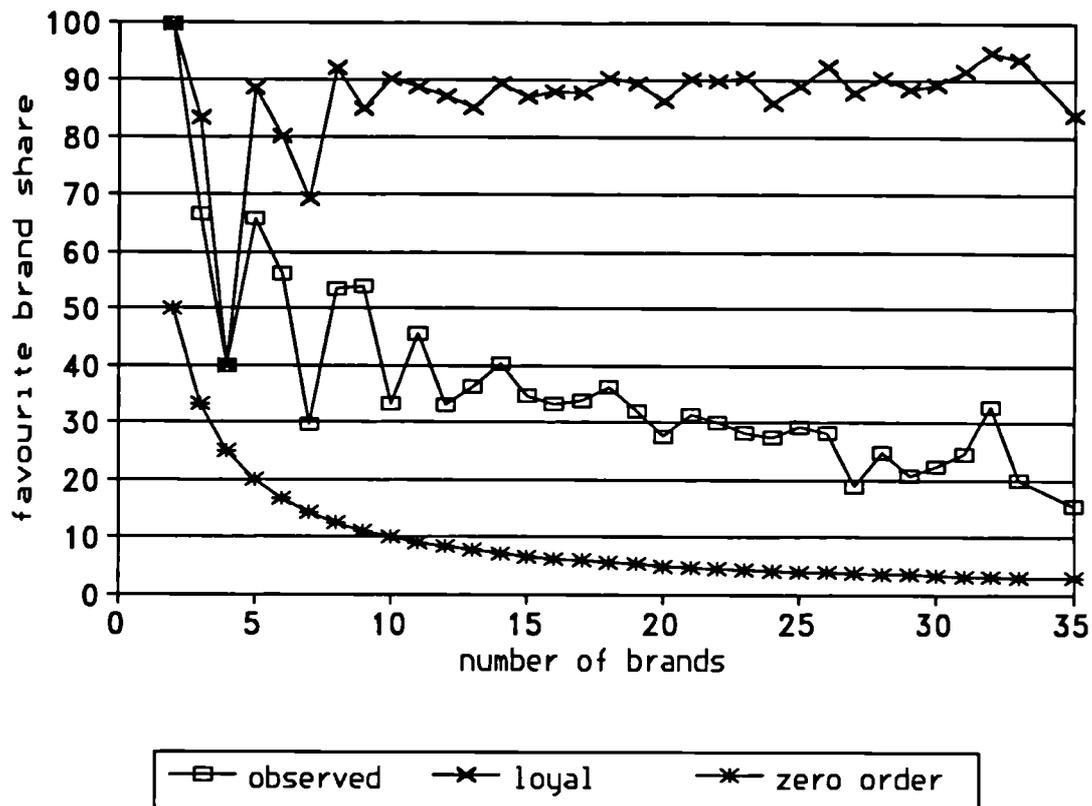
and

$Y = \frac{100}{X}$  when the prescribing behaviour is as close as possible to zero order

where Y is the share of purchases devoted to the favourite brand, X is the number of brands in the consideration set and T is the total number of product class purchases.

By computing the actual shares of the favourite brand and comparing these with the shares which would be expected for the loyal and zero order limit models, one can see how the relationships change with increasing consideration set size. Figure 10.1 shows a plot (observed) of the average share accounted for by the favourite brand for all of the musculo-skeletal categories combined in a year. The data points represent the share accounted for by the favourite brand averaged across the doctors who had used that number of brands in their consideration sets. It also shows the curve (zero order) which would be expected if doctors devoted equal prescription shares to all the brands used, and also the curve (loyal) which would result if the doctor devoted the maximum to the favourite brand, given the consideration set size and the total number of prescriptions. It can be seen that when the consideration set is small, the observed line is closer to the 'loyal' model and when the set is large it is closer to the 'zero order' model.

Figure 10.1. Musculo-skeletals in a Year  
Share of the Favourite Brand



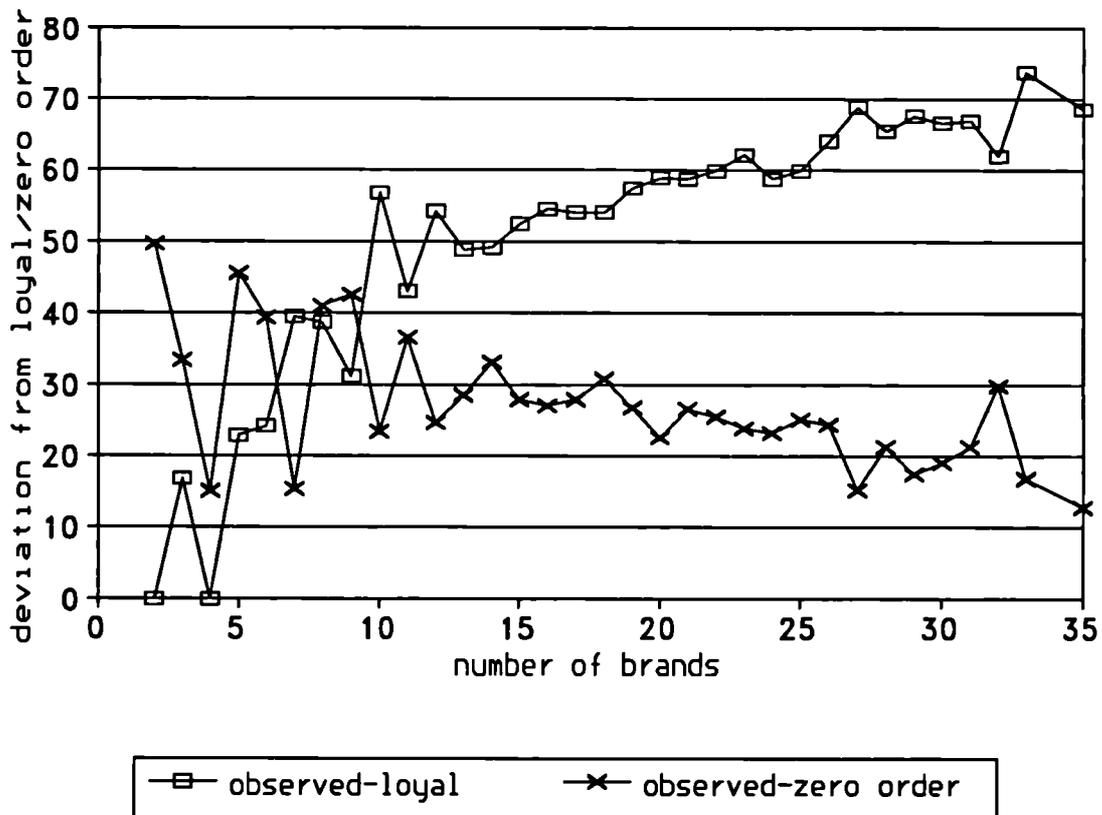
Looking at figure 10.1 it is notable that the 'loyal' model tracks most of the specific variations in the observed data, while at the same time the overall trend is for the two curves to deviate. The reason for this is due to a small number of doctors having the specific consideration set size, one of whom is either an exceptionally frequent or infrequent prescriber.

Figure 10.2 plots the deviations of the observed favourite shares from the 'loyal' and 'zero order' model showing a cross-over point at around six brands.

It is interesting to note that if the limit of the consideration set was determined as six brands (ie within the range of most prior empirical studies of consideration sets such as those considered by Hauser and Wernerfelt, 1990) then one would conclude that on average doctors

depended heavily on one brand, and used others occasionally, ie they exhibited loyal behaviour. Extending the consideration set size, however, leads to the conclusion that prescribing behaviour exhibits much lower levels of loyalty, although it does seem that there is a base level of between 20-30% of prescriptions devoted to the favourite brand, which is indicative of a degree of 'loyalty' inherent in such markets.

**Figure 10.2. Musculo-skeletals in a Year  
Deviations from the Loyal and Zero Order Models**



The implication of these findings for marketers is that consideration set membership is just the first step in becoming a successful brand. In the long run doctors have a favourite brand which accounts for more prescriptions than a pure zero order process would predict. The marketing task here is to develop favoured brand status in a sufficient number of doctors.

### 10.8 Conclusions

This chapter has shown that drugs are prescribed in very similar ways in different product classes by the same doctors. This is despite the fact that there is little correlation between prescribing frequency for the same doctors in the different product fields and diagnoses (see Section 3.3)

After taking the size of the product class into account, there is no significant difference in the number of prescribers, the average prescription frequency, the share of requirements or the rate of sole prescribing that drugs of similar shares will command.

There is evidence of a generic proneness in pharmaceutical prescribing. The effect is weak and non-exclusive, but it is a new finding which is consistent with the private-label proneness described by Ellis (1989).

Further research is needed to see whether the similarities extend to other product classes and also whether generic proneness has changed through time and as a result of environmental pressures on doctors.

This chapter also explored the role of the doctor's favourite brand in the consideration set which in the very short run is all about the likely choice at the next (imminent) prescription opportunity. The favourite brand at the next choice is absolute in that one will by definition observe loyalty. As the number of prescribing events increases, one would expect the patterns across consumers to start to reflect long term brand shares, which in a stationary market would be effectively modelled as a zero order process. The interesting finding here is that there does seem to be some 'residual loyalty' as the favourite brand's share stabilises at around 20-30%, on average, irrespective of the number of brands in the consideration set. This may be connected with the finding that even with

very high usage levels and large consideration sets, doctors still tend to use less than one third of the brands available to them.

The apparent change in tendency when the number of brands in the consideration set exceeds 6 in number is worthy of note. It is not clear whether it is a real shift in consumer behaviour or just a practical illustration of the assertion that short-term behaviour exhibits elements of loyalty when compared to apparent long-term disloyalty. This research would indicate that consideration set studies which used small set sizes could erroneously generate a normative model which encouraged managers to assume degrees of loyalty which were inappropriate within the context of developing brand strategies and plans.

**PART IV - DISCUSSION, CONCLUSIONS AND SUMMARY**

**CHAPTER 11 - DISCUSSION AND CONCLUSIONS**

**CHAPTER 12 - IMPLICATIONS AND FURTHER RESEARCH**

## **CHAPTER 11: DISCUSSION AND CONCLUSIONS**

### **11.1 Introduction**

### **11.2 The Patterns of Prescribing**

### **11.3 Prescribing Pharmaceuticals and Buying Groceries - is the Hypothesis of Similarity Supported?**

### **11.4 What Does Not Appear to Influence Prescribing Behaviour.**

### **11.5 Areas of Knowledge Extension**

### **11.6 Areas of New Knowledge**

### **11.7 Other Findings**

### **11.8 Conclusions**

### **11.1 Introduction**

**Section 1.2** laid out the three key objectives of this thesis, and these are re-stated here. Firstly, it aims to establish the patterns of prescribing behaviour of general practitioners. Secondly, it aims to confirm or refute the hypothesis that the ethical pharmaceutical market behaves like previously studied fast moving consumer goods markets. Thirdly, it aims to discover which factors do not influence prescribing behaviour, in order to flesh out an understanding of this market. **Sections 11.2-11.4** discuss the results in the context of these three objectives.

**Section 1.10** proposed several areas where the current research could extend knowledge of buyer behaviour. These are summarised again here in table 11.1 and **Section 11.5** examines each of these in turn.

**Table 11.1            Areas of Knowledge Extension**

- |  |
|--|
| <ul style="list-style-type: none"> <li>a. Industrial marketing application</li> <li>b. Focus on individual buyer behaviour</li> <li>c. Buyer behaviour across two product classes</li> <li>d. Brand versus generic buyer behaviour</li> <li>e. Segmentation</li> </ul> |
|--|

**Section 1.10** also listed areas of new knowledge to be examined by this thesis, and again these are summarised here in table 11.2. These areas are considered in **Section 11.6**.

**Table 11.2            Areas of New Knowledge**

- |   |
|---|
| <ul style="list-style-type: none"> <li>a. Usage segmentation</li> <li>b. The role of distribution</li> <li>c. The size of the buying unit</li> <li>d. Short inter-purchase timing</li> <li>e. A case of breaking the rules</li> <li>f. The role of the favourite brand</li> </ul> |
|---|

During the course of the study other analytical opportunities arose, and these are considered in **Section 11.7**. The chapter ends with general conclusions.

### **11.2 The Patterns of Prescribing**

Chapters 3 & 4 established the patterns of pharmaceutical prescribing for new and changes of prescription during 1986. The patterns were found to be consistent across the two product fields. The patterns are summarised in table 11.3.

The restriction of the market definition to new and changes of prescription was discussed in **Section 2.7** and while the patterns for repeat prescribing could be different to those discovered here, there now exists an established set of norms against which such patterns could be compared as and when the data becomes available for analysis (see **Chapter 12**).

The restriction of the analyses in this thesis to a year means that longitudinal generalisation can only be tentative. In the case of the current research, however, the frequency of prescription is very much larger than most prior studies and the time period does provide new insights into buying behaviour (see **Section 11.3**). The general body of knowledge that has been built up over the years has shown that overall buying patterns tend to be similar across time. This means that it would be surprising if radically different prescribing patterns were found in subsequent years, as this would mean that 1986 was atypical in a major way.

The other context specific issue is the limitation of the research to two product fields and eight diagnoses. This means that any results and conclusions are strictly confined to these areas. The results that derive from the current research are inherently interesting and so wider generalisation is not a significant limitation. Also, given the similarities with buying behaviour in very different

markets (see Section 11.3), it seems reasonable to assume that the patterns of prescribing for other conditions are likely to resemble those in this thesis. It is predicted that the current results will generalise when other product fields are analysed.

In addition, the rationale for the choice of product classes for inclusion in the analysis (see Section 2.5) means that the current research looks at a range of disease types from acute non-recurring muscle strains to chronic heart conditions which require long term therapy. The consistent patterns which emerge from these, imply that other classes of disease are unlikely to exhibit radically different patterns.

A further consideration is that similar patterns have been found for all eight different diagnoses and the two product classes which cover a very wide range of prescription frequency. In this way the current research has, to an extent, established generalised findings.

The validity of the methodology adopted and the data source used has been justified in Sections 1.7 and 2.3 and also Chapter 5, and this means that the results and conclusions of the thesis should prove robust.

If subsequent research into other product classes proves feasible, then (like the issue of consistency through time) there are now established patterns against which the new data could be compared.

The methodology followed, together with the data sources used seems robust enough to predict that similar patterns will be found in the same data in subsequent years, different product classes in the UK, and in prescribing in different countries (see Chapter 12).

**Table 11.3      Patterns of Prescribing**

- a. Aggregate stationarity.
- b. Individual heterogeneity independent of practice size.
- c. Heterogeneity exists at the level of diagnosis and also product class.
- d. Brands and generics are prescribed in similar ways.
- e. Prescribing cannot be categorised according to key demographic variables.
- f. Heavy prescribers use more different drugs than light prescribers.
- g. Drugs are prescribed in similar ways once their market share is taken into account.
- h. Double Jeopardy is the norm.
- i. Drugs differ more in penetration than prescription frequency in a week.
- j. Large drugs differ more in prescription frequency than penetration in a year, but small drugs differ more in terms of penetration levels.
- k. The distribution of prescription frequencies is reverse 'J' shaped and similar for drugs, diagnoses and the two product classes.
- l. One branded drug, Capoten, stands out as apparently being different to the others.
- m. Drug prescriptions follow the 'Natural Monopoly' effect.
- n. In general there are no drugs which appeal to a niche of prescribers.
- o. Large brands account for higher proportions of their prescribers' needs than do small brands.
- p. There is no evidence of any strong market partition which would demand a segmented marketing approach.
- q. There is evidence of some partitioning between specific drugs or forms of the same drug.

### 11.3 Prescribing Pharmaceuticals and Buying Groceries- Is the Hypothesis of Similarity Supported?

Most of the patterns in table 11.3 are similar to those found in prior research into buyer behaviour in fast moving grocery markets.

Chapters 6-9 provide numerous striking similarities to fmcg patterns (see Section 1.9) which are well modelled by the Dirichlet. The empirical results along with the fit of the Dirichlet give strong support to the above hypothesis.

This section focuses on four of the patterns in table 11.3 which show some unexpected similarities with, or differences from patterns found in fmcg markets. These are individual heterogeneity, variation in prescription frequency rather than penetration, the brand Capoten, and lastly, the prescribing of brands and generics.

#### a) Heterogeneity

One of the key assumptions underlying the NBD part of Dirichlet theory (see Chapter 5) is that individuals have a purchase probability which can be modelled as a Poisson process. A product market is comprised of individuals with different Poisson means and this leads to the distribution of purchases for individual brands which follow the NBD. The nature of the distribution tends to be highly skewed capturing the heterogeneity which is observed in the market.

This heterogeneity extends across product classes so that a frequent buyer of detergent may not be a frequent buyer of washing-up liquid. Heterogeneity is usually explained in terms of subjective propensities so that (for example) some households happen to contain members who like coffee very much and therefore consume it frequently.

Starting to think about prescribing (without the data), it might have been deduced that the long training and professional standards of doctors would lead to behaviour that was homogeneous in comparison with households making

relatively unimportant purchasing decisions. Faced with a broadly similar set of diagnostic situations it might have been expected that doctors would write broadly similar numbers of prescriptions. In addition, one might have expected to see doctors using a similar (small) number of drugs to satisfy these 'similar' prescribing needs. Finally, while it seems reasonable that a heavy coffee buyer need not be a heavy tea buyer, would it be expected that a doctor who prescribes frequently for heart disease does not do so for osteo-arthritis?

In this context, the findings of Chapter 3 are really quite remarkable as they reveal very high degrees of heterogeneity. At the same time it was possible to test directly the Poisson assumption of the NBD. Chapter 3 also indicated that doctors vary greatly in the number of drugs they use and that there is no correlation between individuals' prescribing frequencies across diagnoses or product classes.

The current research has established that doctors exhibit heterogeneity consistent with Dirichlet assumptions. It has also provided direct evidence to support Poisson purchase behaviour (see Section 11.7c). These are both substantive findings.

Understanding the reasons behind this heterogeneity remain outside the scope of this thesis and will be considered as an area for further research in Chapter 12.

#### b) Growth and Variability of the Components of 'Sales'

The results in Sections 4.3 and 4.8 showed up some interesting differences between prescribing pharmaceuticals and buying groceries. Where the rates of prescription are very frequent, the increase in 'sales' through time for large share drugs derives more from increased prescription frequency than penetration. This compares to the growth in

sales for most fmcg markets which derives more from increased rates of penetration than buying.

A related finding is that individual drugs which have large prescription shares vary more in terms of the average frequency with which they are prescribed than the number of doctors they have as users. Again, the reverse is the norm in prior research.

These contrasts are understandable in terms of frequency of 'purchase' and time, rather than any intrinsic nature of the markets, and the results are patterns which are consistent despite the differences.

**Chapter 4** related these two patterns to the penetration levels which for large share drugs in very frequently prescribed product classes could exceed 50% in a quarter. This means that in a year 'sales' growth has to be driven more by frequency than penetration.

**Chapter 6** went on to successfully model these two effects using the Dirichlet, showing that if reliable long run grocery market panel data is made available then similar patterns would be expected.

#### c) The Exceptional Brand Capoten

The methodology and modelling approach adopted helped to identify that Capoten was prescribed differently to the other cardiovascular drugs during 1986. **Chapter 9** was devoted to analysing and explaining the nature of the exception which can be understood in the context of a long term and successful promotion specific to the brand.

While the deviations from Dirichlet norms were much larger than any previously reported, they mainly affected penetration and purchase frequency and other prescribing behaviour measures were still quite close to those predicted.

As 1986 progressed and the post marketing campaign promotion abated, the deviations became less pronounced and it seems likely that Capoten would revert to the Dirichlet norms for drugs used in the control of hypertension. Further research covering subsequent years would test this prediction (see Chapter 12).

There was one other drug which showed significant deviations from Dirichlet norms which were almost as large as those of Capoten. Chapter 8 showed that Ibuprofen, a generic drug, was prescribed as expected in two out of the three musculo-skeletal diagnoses but in the third diagnosis it had high average frequency and low penetration for its prescription share. It is interesting that the branded version of the same drug, Brufen, was prescribed largely according to Dirichlet norms, and while it would be useful to repeat the analysis in subsequent years to see whether Ibuprofen remains different to other drugs, this finding shows that it is possible for a generic to be prescribed in ways which resemble a brand which is the subject of a programme which made it definitively different from the other drugs on the market.

#### d) Brands and Generics Compared

The immediately preceding discussion point leads to the consideration of one pattern which was evident in the current research. This pattern has not been observable in the same way in prior studies although the examination of private labels (Ellis, 1989) in a different market situation provides an interesting comparison.

Chapters 4 and 8 demonstrate that (with the exception of Ibuprofen in one diagnostic situation) there is little difference in the way that brands and generics are prescribed. The differences which are apparent are in general accounted for simply by prescription shares. There

are, however, two further patterns which also relate to market partitioning as discussed in **Section 11.5d** below.

#### **11.4 What Does Not Appear to Influence Prescribing Behaviour**

The finding that the patterns of prescribing are so similar to those of grocery buying suggests that the differences between the markets do not affect the patterns. The only alternative explanations are either that the different factors interact together in some complex way which results in the similarities, and this seems unlikely. Or, that some features of the Dirichlet model's mathematics result in the ability to model very different markets as if they were similar. Even if this occurs, the predictions are close to observed patterns and this makes the model of practical use.

One way to characterise the differences between the markets (others are described in **Sections 11.5** and **11.6**) is to compare the elements of the marketing mix.

##### **a) Product**

Similar drugs are chemically distinct and often protected by patent, whereas grocery brands are often identical apart from the package. This fundamental difference does not result in different patterns of behaviour. Prescription shares, like brand shares are the key to a whole range of different measures of behaviour.

##### **b) Price**

Doctors do not pay for the prescriptions and at the time of data collection they were largely indifferent to the price charged to the NHS by the drug company. Groceries compete for consumer purchases at least partly on price. As the patterns are similar, this means that while price can play a significant role, other factors dominate the patterns of behaviour. A tentative connection might be made between the role of price and the generic propensity described in **Chapter 7**, bearing in mind that the size of the effect is small.

### c) Distribution

In one sense, doctors are like retailers without stock, deciding which brand the customer will receive. This contrasts with the consumer selecting a brand from those available on the supermarket shelf. This means that the drug manufacturer does not have to ensure availability in the same way that a grocery manufacturer must. The latter would lose a sale, as unavailability would mean the purchase of an alternative brand. Despite this difference the patterns remain similar, and so they do not appear to be a key determinant of behaviour.

### d) Promotion

As described in Chapter 1, the amount of expenditure on drug promotion is limited by the government and the industry association to which all drug manufacturers belong also operates a code of practice to ensure that standards are maintained. At the time of the data collection, advertising was limited to journals and direct mail.

Grocery markets are largely free of promotional restrictions with profit impact and competitive activity largely determining the levels and forms of promotion.

The major difference between drugs and groceries is the direct contact which pharmaceutical companies maintain with their 'customers' via sales forces.

Despite these differences the buying/specifying patterns are similar.

If the post-marketing campaign for Capoten is categorised as a promotion, then there is some evidence of an effect not usually found in grocery promotions, in terms of both length and form of response (see Section 11.3).

Other points of difference are discussed later in this chapter, but the conclusion that a radically different set of market conditions give rise to similar patterns is indicative of the range of factors which appear not to influence buying behaviour.

One interpretation of these findings would be that elements of the marketing mix are less important in shaping buyer behaviour than some theorists or practitioners would like to believe. Such a conclusion does not remove the need to develop and promote brands competitively and ensure that they are available. It does, however, support the view of marketing activities as primarily defensive (Ehrenberg and Goodhardt, 1979), in these types of market.

In this way, the marketing might have the avoidance of competitive disadvantage in the eyes of the consumer as its prime objective. If any combination of the mix elements can be developed in such a way as to make imitation relatively more costly or hard for competitors to copy, then a "differentiation" advantage may be an added bonus.

### **11.5 Areas of Knowledge Extension**

#### **11.5a Industrial Market Application**

Because of the structure of the market and the direct relationship between the pharmaceutical company and the G.P., pharmaceutical prescribing exhibits elements of an industrial market (see **Section 1.10a**) and hence differs fundamentally from fast moving consumer markets.

Despite these differences the patterns of behaviour are predictably similar and so the current research extends knowledge about how stationary industrial markets might be described. One further testable example would be bulk purchases of cars by fleet buyers (see **Chapter 12**).

The results show that pharmaceutical prescribing in the UK may be added to the number of industrial applications which

have been modelled by the Dirichlet, in addition to the already impressive list of consumer markets.

#### 11.5b Focus on Individual Buyer Behaviour

The prior evidence suggesting that individuals buy in similar ways to households (see Section 1.10b), is clearly supported by the results in Chapter 6. The current research also extends knowledge further as the doctor is specifying as opposed to buying, and yet the patterns are, in general, the same.

#### 11.5c Buyer Behaviour Across Two Product Classes

The current research builds upon the limited knowledge in this area. The rates of prescribing across the two product fields showed low correlations consistent with the gamma assumption of the Dirichlet (see Section 3.3).

The structure of the data by diagnosis permitted the experiment conducted in Chapter 10 which showed that the Dirichlet effectively models prescribing behaviour of completely different types of drug in the same analysis.

One implication is that the prescribing behaviour in therapeutic areas where data is not available could be simulated as long as the overall rate of prescribing can be estimated (see Chapter 12). Such simulations might extend beyond prescribing behaviour to other markets.

#### 11.5d Brand versus Generic Buyer Behaviour

Another conclusion from studying prescribing behaviour across the two product fields was that doctors who prescribe a generic drug in one product class are more likely to prescribe it in the other than the population as a whole. This is similar to findings on the buying of own labels (Ellis, 1989).

A further finding was that doctors who prescribed one generic drug within a product field were some 20% more

likely to also prescribe other generics in the same product field than the population as a whole.

These two findings indicate that there seems to be a general generic partition in pharmaceutical prescribing and this is a result of interest to academics and practitioners.

Doctors' behaviour in prescribing both the branded and generic form of the same drug was examined. It was found that, for musculo-skeletal, a doctor who prescribed a branded version was less likely to also prescribe the generic version of the same drug than the population as a whole. The tendency was not absolute so that many doctors prescribed both forms. There were no similarly "clear" patterns for cardiovasculars.

Individual brands and generics were also analysed and no major differences were found in the ways that they were prescribed. The behavioural measures were predictable from the prescription shares which were dominated by brands. Brands do not attract higher levels of loyalty than generics once their market share is accounted for.

#### 11.5e Segmentation

The nature of the market led to the hypothesis that some brand pairs might exhibit relatively high duplications in response to prescribing two drugs at the same time. If confirmed, this would provide a rationale for the production of combined product forms.

The analyses did not reveal any such brand segmentation, and **Section 4.9** concluded that there was no special tendency for a doctor who prescribes a drug with one active ingredient to also prescribe a preparation with the same active ingredient in combination with another.

## 11.6 Areas of New Knowledge

### 11.6a Usage Segmentation

The diagnostic choices made and recorded by doctors gave rise to the duplication analyses conducted in Chapter 7. These showed a weak market partition where doctors who prescribed a drug for one musculo-skeletal diagnosis were more likely to also prescribe the same drug in a different diagnosis than the population as a whole. The effect was weaker in the case of cardiovasculars, but this is the first time that segmentation by use has been identified in research based on panel data.

The finding is especially interesting because it describes a pattern of using the identical product in different situations. There will be direct parallels in consumer markets (such as using condensed soup to make soups or sauces) but they would be impossible to analyse because of the nature of the purchase data.

The fact that the partition exists but is so weak in drug prescribing, may have implications for critically evaluating attitudinal research which claims to find segmentation and positioning opportunities based on usage. It may also help in the analysis of brand extensions and consumer franchises, where the analysis would differ in that the product as well as the usage would vary. One would predict from the current research for example, that any partition of buyers of a core brand and the category extension would be of a minor form and that the individual category buying patterns would dominate the analysis.

It should also be noted that the partition is general and not associated with an identifiable segment of doctors, and as such it does not necessarily provide the means to develop strategies based upon segmentation.

#### 11.6b Distribution Channel

The discussion in **Section 11.4** indicated that the current research has not identified any new patterns caused by the very different role of distribution in pharmaceuticals when compared to consumer goods.

A related distribution issue is that of comparing the turnover of a grocery category in an individual supermarket to musculo-skeletal prescribing. An annual turnover of 50,000 units (1000 per week) would not be an unusual figure and so it might be possible to start to describe the buying patterns within a supermarket from those established in the current research.

#### 11.6c Size of the Buying Unit

Prior studies have used small buying units (which are also the consumers) based upon the nuclear family as the unit of analysis. The situation with pharmaceutical prescribing is very different because the doctor is a single person specifying for the needs of several thousand 'family members'.

There was no reason to suppose that similar 'buying' patterns would result from such a different situation, but this is what has been established. Given the nature of the differences between the buyers of consumer goods and the prescribers of drugs, it seems unlikely that more similar situations (lecturers recommending textbooks for students, for example) would result in radically different patterns.

#### 11.6d Inter-purchase Timing

The short inter-prescription timing for musculo-skeletals equates to a typical consumer market over a very long period (see **Section 1.11d**). This means that the current research might be used to help understand elements of these markets over the long term. As it is unlikely that they would remain stationary throughout the period, generalisation must be tentative.

The findings discussed in Section 11.3 are examples of using the established Dirichlet theory together with the current research to understand the way that the components of sales might be expected to grow in the very long term. In this case, the theory was used as a predictive tool and the current research confirmed the theoretical prediction.

#### 11.6e A Case of Breaking the Rules

Analysis by penetration and prescription frequency identified the brand Capoten as different to others and one which consistently failed to match Dirichlet norms.

Chapter 9 analysed Capoten in some detail and showed a possible reason for the differences associated with this brand. The post-marketing study can be compared to a highly successful long term consumer promotion, which managed to target a relatively small number of frequent prescribers. The current results are different to prior studies on promotions which were seen to attract a surfeit of light buyers (eg Ehrenberg and Goodhardt, 1979).

The mode of operation of the post-marketing study resulted in Capoten being significantly different to other brands in that prescribing the drug was associated with being 'loaned' a computer. Seen in this light, it is perhaps surprising that the patterns of prescribing for Capoten were not even more different.

#### 11.6f The Role of the Favourite Brand

The analysis of the share of total prescriptions accounted for by the favourite brand used by each doctor indicated that it was higher than predicted by a pure zero order process. Given the success of using the Dirichlet to model prescribing behaviour this finding is of interest, and is a subject of the recommendations for future research in Chapter 12.

## 11.7 Other Findings

### 11.7a Differentiation

The analysis of market share by diagnosis in Chapter 7 revealed that the market structure of cardiovasculars and musculo-skeletal were quite different. Large share drugs in musculo-skeletal had large shares in most of the diagnoses, and small share drugs had small shares in most diagnoses. Large cardiovascular drugs had a large share of one diagnosis and some small share drugs still had a significant diagnosis share.

The data source has therefore revealed an undifferentiated and a differentiated product market. In the latter, it seems that drugs exist by satisfying a specific rather than a general need, and as such, fill a market niche. It should be stressed however, that the niche is due to a defined use, rather than being based upon a unique segment of the population whose prescribing needs are met by the particular drug.

There is a relationship with the market partitioning described in Section 11.6a in that the partition is more marked in the undifferentiated musculo-skeletal product market, whereas in the differentiated cardiovasculars the partition is weaker. In this respect the finding might run counter to the established view that highly differentiated markets are also highly segmented. Further work is required to understand these findings as is the fact that the Dirichlet fits a differentiated market (all cardiovasculars) as well as the undifferentiated musculo-skeletal therapeutic area.

### 11.7b Combining Diagnoses to Make the Product Class

In prior studies, the Dirichlet has been used to model brands which are highly substitutable and similar. It is this similarity which is used to help explain the patterns of Double Jeopardy seen in numerous product markets.

In the current research, Double Jeopardy has been described and modelled for all eight diagnoses and it is clear that they are very different. This provides a further application of the Dirichlet.

In addition, the cardiovascular product field was combined with Rheumatoid Arthritis and very different drugs still show the Double Jeopardy pattern. This develops the findings of Ellis (1989) who combined fruit squash and fabric conditioners in the grocery markets (see also **Section 11.5c**).

#### 11.7c A Direct Test of the Poisson Assumption

The current research permits a direct test of the Poisson assumption of the Negative Binomial Distribution for the first time because of the high musculo-skeletal product class prescription frequencies. **Section 5.2** showed that for the majority of doctors the Poisson is a good approximation of actual behaviour.

#### 11.7d Frequency of Prescribing and Portfolio Size

**Section 3.8** showed the relationship between frequency of prescribing and the number of brands used by doctors. A positive association would be expected and was indeed found and modelled. The relationship between the portfolio size (consideration set), the rate of prescribing and the share of the favourite drug remains to be examined in detail and is the subject of further research (see **Chapter 12**).

#### 11.8 Conclusions

The patterns of pharmaceutical prescribing are largely predictable from Dirichlet theory. Prescribing is very similar to buying groceries but there are some interesting differences and the analyses help to predict the nature of consumer markets in the long run.

The thesis also demonstrates an example of a brand being prescribed differently to other brands.

The current research has extended the range of applications of Dirichlet theory, extended knowledge about the way markets behave and proved a source of new knowledge which will hopefully contribute to marketing theory and practice.

The patterns of pharmaceutical prescribing are largely predictable and similar to grocery purchases. A whole range of differences in market structure are not reflected in the patterns of buying and prescribing.

An analyst confronted with a market which shows little or no overall sales trend should start by asking what unique features exist which would lead to patterns different from those predicted by Dirichlet theory.

**CHAPTER 12: IMPLICATIONS AND FURTHER RESEARCH****12.1 Implications for Marketing Research****12.2 Implications for Pharmaceutical Marketing****12.3 Implications for the Profession****12.4 Implications for Policy****12.5 Further Research**

### 12.1 Implications for Marketing Research

The current research has fruitfully revealed a number of findings, some of which are new and others which are extensions of existing knowledge about buyer behaviour.

The process of using empirical patterns as the basis for theory development which is then used to test new data (the Empirical then Theoretical then...(ETE) research tradition, Ehrenberg, 1993) was followed in the current thesis. The subsequent dissemination of the results will hopefully encourage others to follow the same route and so extend the expanding body of knowledge in the area.

While there are some novel findings in the thesis, most of the results are not. They are new, but familiar and yet it is these which contribute more to the extension of general knowledge about market structure and behaviour.

As well as extending understanding of buyer behaviour, the current research should lead to further development of Dirichlet theory as the issue of modelling both differentiated and undifferentiated markets is explored in the future (see Section 12.5).

The meta-analysis of Fader's (1993) integrative model conducted in Chapter 5 demonstrated the limited value of a more complex but related model. This suggests that the simple Dirichlet should be used as a benchmark when evaluating marketing models of buyer behaviour. One research task is, therefore, to determine the difference in degree of fit and whether this should lead to the abandonment of the simple Dirichlet model, or else its retention.

The current thesis also lays the foundation for contributing to the understanding of how buyers allocate their choices within their consideration set of brands. This could lead to a further successful application of Dirichlet theory.

## 12.2 Implications for Pharmaceutical Marketing

The findings of the current research have a range of implications for pharmaceutical marketers. Firstly, the established patterns permit comparison with competitive brands in order to evaluate performance for a given market share. Secondly, the patterns can help to understand the limits to growth for any particular drug depending on the degree of differentiation which exists. The Dirichlet norms can also be used in setting sales targets for new brand launches or extensions of use into new diagnostic situations.

The results of the current thesis may call into question some of the attitudinally based segmentation schemes which have been developed by other researchers (eg Maier, 1989) or those used in practice (Corstjens, 1991). There are three potential problems. Firstly, heavy prescribers in one diagnosis are not necessarily heavy prescribers in another diagnosis within the same therapeutic area. Furthermore, a heavy prescriber in one therapeutic area may not be a heavy prescriber elsewhere. This means that attitudinally based segmentation models which attempt to classify by weight of prescribing for one diagnosis are unlikely to be generally valid. Secondly, the degrees of heterogeneity seen in prescribing data imply that the very heavy prescribers will use a larger number of drugs (than light prescribers) to fulfil their requirements and loyalty levels will vary little from drug to drug. This means that a strategy to target heavy prescribers with a view to instilling loyalty is unlikely to succeed. Thirdly, as there is no published evidence to support the consistency of reported and actual prescribing behaviour, this means that where possible, attitudinal studies require validation from sales data and preferably panel data.

The performance of Capoten in 1986 does show the degree to which prescribing frequency can be affected in this market although it is highly unlikely that the regulatory

authorities would permit such activities in the UK today. Other markets which are less regulated might be susceptible.

In terms of product development opportunities, **Chapter 4** showed that doctors who prescribe a drug in one strength are more likely to also prescribe the same drug in a different strength than the population as a whole and this indicates that such a strategy is worth pursuing when there are real consumer benefits (ie requiring one dose instead of two). The current research indicates that such partitioning is of a general nature and not likely to be susceptible to categorisation and thus segmentation.

In a similar vein **Chapter 4** also examined duplications between prescribers of one drug and a second which also contained added ingredients. In some cases a partition was found, but this was not general and the conclusions are similar to those reached for marketing the same drug in different strengths. Marketing a combined drug should be based upon a general market need and not be targeted at a specific group of doctors.

As drugs reach the end of their patent protection, marketers must decide how to respond to increased generic competition. Tracking the way that doctors prescribe the drug (in its branded and generic form) may help to time any changes in the offering.

The method of market analysis followed in this thesis helps to compare and highlight differences in brand performance and could form the basis for setting sales targets and matching objectives in terms of penetration and prescription frequency.

The Dirichlet could also be used as a simulation to help plan new brand launches in therapeutic areas of which a drug company has little experience. This would extend to distribution agreements as well as new chemical entities.

### 12.3 Implications for the Profession

This thesis had description rather than explanation as one of its objectives. Having now established these patterns, doctors could potentially evaluate what they do against some 'best practice' set by expert professionals.

In a related issue, the profession might be interested in discovering the reasons behind the prescribing heterogeneity found in this research, and this is one area identified for future work (see Section 12.5).

The current research may help the profession in developing its views about the promotional activities of pharmaceutical companies. The patterns of prescribing do not support the belief that representatives are making doctors permanently 'switch brands'. If promotional activities are primarily seen as defensive and protecting the market share of individual drugs, then in general they are part of the costs of competition. In this respect doctors can distance themselves from any debate with the caveat that sufficient safeguards exist to prevent marketing activities which would act against the best interest of the patient.

### 12.4 Implications for Policy

The promotion issue is relevant to policy makers as well as the profession. There seems to be no defined rationale to support the current restrictions on expenditure by pharmaceutical companies. Given the desire to control the cost of drugs, some restriction is understandable as a way of ensuring that large companies with potential economies of scale do not drive out smaller competitors, thereby reducing the level of competition and resulting in higher prices.

Given the patterns observed for Capoten in the current research, an alternative strategy to promotional limitation would be to monitor brand penetration and prescription frequencies using the Prescription Pricing Authority data

and the Dirichlet to highlight incidences where brands deviate from the norms. This might then operate as a regulatory and investigative mechanism.

Policy makers have tried to reduce the expenditure on drugs by encouraging generic prescribing through banning some brands from NHS prescription. Such restrictions inevitably induce responses about limiting choice without any empirical evidence on outcomes. The approach of the current research could be extended to look at branded and generic prescribing through time so that an analytical basis exists for evaluating such policy decisions. The generic partitions described by the current research do indicate that there is a tendency which already exists and should therefore be capable of further development. On the evidence of the current research, one strategy for increasing generic prescribing would be to focus on undifferentiated therapeutic areas.

There are an increasing number of drugs which are being made available without prescription through pharmacists. One concern is that consumers lack the knowledge to choose drugs and that their choice patterns are different to those of the trained doctor. The current research indicates that doctors already prescribe with patterns similar to those of consumers and so this would be an inappropriate reason for restricting the development of pharmacy based availability.

The heterogeneity of G.P. prescribing may also be of interest to policy makers. If there is no generally accepted medical rationale why prescribing rates should vary by a factor of 100 then it would be possible to set a range of prescription frequencies for each therapeutic area so that volume as well as total cost is taken into consideration.

### 12.5 Further Research

The current research has inevitably raised a number of questions which can only be answered after further study. Some are related to prescribing behaviour and others have more general concerns.

The first set of potential projects involve analysing the same data source in subsequent years to examine the issues in table 12.1.

**Table 12.1 Further Research Using the Jigsaw Database**

Is Capoten still different?  
 Is Ibuprofen still different?  
 Do the other therapeutic areas share the same patterns?  
 Do the same patterns hold through time?  
 Do the generic partitions persist?  
 What is the impact of product innovation?

It should be possible to use the Dirichlet to predict the prescribing patterns of the other "Jigsaw" therapeutic areas prior to analysis.

Perhaps the most interesting question raised by this thesis is why doctors exhibit such a high degree of heterogeneity in their prescribing behaviour. A related question is whether or not doctors are aware of such heterogeneity. Both these questions could be tackled using small group discussions based on some of the results of the current thesis.

More generally, it seems that pharmaceutical prescribing would be an ideal market to test the coincidence of attitudes and behaviour and also try to explain any large differences. Previous research (eg Wind and Lerner, 1979) has found low levels of agreement between attitude and behaviour but not explored the reasons. Other studies have

started to examine such patterns (eg Barwise and Ehrenberg, 1985; Castleberry and Ehrenberg, 1990), and further research would not only advance knowledge by replicating previous work in a different field, but could start to help explain why such differences occur.

Knowledge of prescribing behaviour is still very limited and yet Government data does exist at the individual prescription level for 9000 practices in England. This data covers all prescriptions written since 1988 but has only been used as a costing and remuneration mechanism.

A new project using Prescription Pricing Authority data as well as interview data could explore these issues which are summarised in table 12.2

**Table 12.2 Further Prescribing Research Using Other Data Sources**

Do the patterns of the current research generalise to repeat prescribing?

How well do doctors understand what they do?

Why do doctors vary to such an extent in their prescribing rates?

Some or all of these analyses could be extended to other countries for comparison depending upon the availability of suitable data.

Given the finding on combining product fields in Chapter 10, it would be interesting to measure another product-market bought or specified by the research subjects coincident with their prescribing behaviour (eg buying petrol), although it is not clear how this could be done in practice.

Other potential research areas of more general interest are listed in table 12.3

**Table 12.3 Further Research of General Interest**

Do the general patterns hold for other types of product-markets?

Why does the Dirichlet work for an aggregate market with underlying structure like cardiovascular prescribing?

What is the role of the 'favourite' brand in the consideration set, and can the Dirichlet successfully model this pattern?

What are the implications of segmentation by use coinciding with an undifferentiated product market?

The last two of these issues are already being addressed and the second is seen as a priority for the future.

**APPENDIX 1: CHRISTMAS****A1.1 Introduction****A1.2 Patterns of Prescribing at Christmas****A1.3 Conclusions**

### A1.1 Introduction

In Chapter 2 it was noted that the two weeks of Christmas were atypical and were removed from the analysis. This appendix is devoted to exploring the differences and showing that the Dirichlet still successfully models these two weeks. This provides a further example of the fit of the model.

### A1.2 Patterns of Prescribing at Christmas

Chapter 2 described how the average weekly number of cardiovascular prescriptions was 300 and the figure for musculo-skeletal was 1000. In both cases the mean deviations were about 10% of the average. The total number of prescriptions written for cardiovasculars in the first Christmas week was 109 and for the second week it was 205. The corresponding figures for musculo-skeletal were 472 and 753. Despite these differences the shares of prescriptions were similar for the Christmas period and the rest of the year as shown in tables A1.1 and A1.2.

**Table A1.1 Prescription Share of Cardiovasculars**

Drug	Christmas Share %	Rest of Year Share %	Difference %
Atenololc	15.3	13.7	1.6
GTN	11.0	9.0	2.0
Nifedipine	10.1	8.8	1.3
Frusamide	7.5	9.7	-2.2
Propranolol	6.0	5.5	0.5
Captopril	5.7	6.2	-0.5
Cyclopentiazide	4.9	3.9	1.0
Bendrofluazide	4.3	4.7	-0.4
ISMO	3.9	3.1	0.8
ISDIN	2.9	2.3	0.6
Digoxin	2.6	2.9	-0.3
Bumetanide	2.6	2.4	0.2
Verapamilc	2.2	1.5	0.7
Mean Average Deviation			0.9

**Table A1.2 Prescription Share of Musculo-skeletals**

Drug	Christmas Share %	Rest of Year Share %	Difference %
Ibuprofen	17.0	17.1	-0.1
Naproxen	11.4	10.1	1.3
Coproxamolc	9.7	8.6	1.1
Paracodeine	7.6	7.2	0.4
Voltaren	6.3	6.3	0
Mefenamic	5.5	4.5	1.0
Piroxicam	5.0	5.3	-0.3
Indomethacin	4.6	5.4	-0.8
Ketoprofen	2.8	3.1	-0.3
Mean Average Deviation			0.5

Overall, the pattern of prescription share differs little from the rest of the year and so using these two weeks as a separate data set, the Dirichlet can be used to model prescribing behaviour at Christmas.

Table A1.3 shows a number of prescribing behaviour measures for cardiovasculars and table A1.4 shows the same data for musculo-skeletals.

The excellent fit of the model to the data for the two Christmas weeks is summarised by the small mean absolute deviations between the observed and predicted values. The high  $R^2$  values for penetrations in both product fields provide a further summary of the model's fit.

Table A1.3 Prescribing of Cardiovasculars

2 Weeks	ms %	b		w		wp		sor*	
		O %	T %	O	T	O	T	O %	T %
Atenololc	15	17	15	1.1	1.3	2.7	3.4	42	37
GTN	11	12	12	1.1	1.2	3.3	3.5	34	34
Nifedipine	10	12	11	1.0	1.2	3.0	3.5	34	34
Frusamide	8	8	8	1.1	1.2	3.0	3.6	38	32
Propranolol	6	6	7	1.3	1.1	3.9	3.6	33	31
Captopril	6	5	6	1.4	1.1	3.2	3.6	44	31
Cyclopentiazide	5	5	6	1.2	1.1	3.8	3.7	30	30
Bendrofluazide	4	5	5	1.2	1.1	3.7	3.7	32	30
ISMO	4	5	5	1.0	1.1	3.5	3.7	29	30
ISDIN	3	4	3	1.0	1.1	2.7	3.7	38	29
Digoxin	3	3	3	1.1	1.1	4.0	3.7	29	29
Bumetanide	3	3	3	1.1	1.1	4.0	3.7	29	29
Verapamilc	2	2	3	1.8	1.1	3.8	3.7	47	29
Average		7	7	1.2	1.1	3.4	3.6	35	31
MAD		0.6		0.2		0.4		4.4	
R <sup>2</sup>		0.98							

\* sor is share of requirements accounted for by that drug, ie Atenololc accounts for 42% of the average doctor's cardiovascular prescribing needs in the two weeks.

Table A1.4 Prescribing of Musculo-skeletal

2 Weeks	ms	b		w		wp		sor	
		O %	T %	O	T	O	T	O %	T %
Ibuprofen	17	38	38	2.3	2.2	7	9	31	26
Naproxen	11	27	29	2.2	2.0	8	9	26	22
Coproxamolc	10	26	26	1.8	1.9	8	9	22	21
Paracodeine	8	17	21	2.2	1.8	9	9	26	20
Voltaren	6	14	18	2.1	1.8	8	9	28	19
Mefenamic	6	14	16	1.9	1.7	9	10	20	18
Piroxicam	5	14	15	1.8	1.7	7	10	26	18
Indomethacin	5	18	14	1.3	1.7	8	10	17	18
Ketoprofen	3	7	9	1.9	1.6	9	10	22	17
Average		20	21	1.9	1.8	8	9	24	20
MAD		1.9		0.2		1.2		4.6	
R <sup>2</sup>		0.95							

### **A1.3 Conclusions**

While the Christmas period differs from the rest of the year in terms of the total number of prescriptions written, the patterns of prescribing are similar. The Dirichlet successfully models prescribing behaviour using prescription shares and the familiar patterns summarised in Section 11.2 are again evident.

This analysis shows that omitting the Christmas period from the main analyses does not affect the conclusions of the current research.

**APPENDIX 2: COMPUTER PROGRAMMES****A2.1 Introduction****A2.2 List of Programmes Written****A2.3 Example Programme**

### A2.1 Introduction

The prescribing data was received in raw form and had to be summarised in order to ascertain the number of drugs which held significant prescription shares. Pre-analysis indicated around 50 different names in each product class were prescribed.

At the start of the research, personal computer processing capacities were limited and the PC version of BUYER in development form was therefore practically restricted in terms of the number of entities which could be included in any analysis.

Initially, the empirical patterns of prescribing were not known and so it was decided to analyse the raw data using industry standard software for which programmes had to be written. In this way the patterns could be examined to see whether or not they were similar to those established by prior research, and therefore suitable for use with the Dirichlet. The package chosen was DBASE 3+ as it was widely available and PC compatible.

With the current availability of PCs with improved processing power it will be feasible to extend the parameters of the BUYER software so that future research will not require recourse to the approach followed by this thesis.

**Section A2.2** lists the programmes written to analyse the raw data and **Section A2.3** reproduces a listing for one of these programmes which was used to generate penetration and prescription frequencies of each drug, along with the product class prescription rates from the raw data.

### A2.2 List of Programmes Written

The key programmes written are listed below, many others were also written for specific applications.

1. Programme to tabulate drug penetration and prescription frequency and also the product class prescribing rate.
2. Programme to tabulate the distribution of prescription frequencies.
3. Programme to tabulate sole prescribing incidence and rates.
4. Programme to tabulate repeat prescribing incidence.
5. Programme to tabulate the favourite brand's share of prescriptions.
6. Programme to tabulate duplication tables for up to 60 brands.

### A2.3 Example Programme

As an illustration of the programming carried out as part of this thesis, the DBASE 3+ programme which tabulates penetration, frequency and product class rates of prescribing is reproduced here.

The raw data is imported into a pre-defined database file called 'BASE' which is then processed along with 7 other blank pre-formatted files (BRAND, DOCTORA, LASTB, SUMB, SUMB1 and SUMB2).

Philmain.prg

```

set safety off

use base
  replace all brand with ltrim(brand)
close data

use base
  copy to base1 fields
    brand,doctor,brandcount,ms,roundms,;
    doccount,docshare,docrnd

use base1
  store reccount() to script
  index on brand to brand
  replace all brandcount with 1, doccount with 1
close data

sele 5
use base1 index brand
  go top
  do while .not. eof()
  store brand to brandx
  count to bra_cnt while brand=brandx

sele 6
use brand
  append blank
  replace brand with brandx
  replace brandcount with bra_cnt

sele 5
  enddo
close data

erase brand.ntx

use brand
  copy to branda fields brand,brandcount,ms,roundms

use base1
  index on doctor to doctor
close data

sele 7
use base1 index doctor
  go top
  do while .not. eof()
  store doctor to doctorx
  count to doc_cnt while doctor =doctorx

sele 8
use doctora
  append blank
  replace doctor with doctorx
  replace doccount with doc_cnt

```

```

sele 7
    enddo
close data

use doctora
    copy to doccount fields doctor,doccount,docshare,docrnd
close data

erase doctor.ntx
erase base1.dbf
erase brand.dbf
erase doctora.dbf

use branda
    replace all ms with brandcount*100/script
    replace all roundms with ms
close databases

use branda
    copy to brandcou fields brand,roundms
close databases

use doccount
    replace all docshare with doccount*100/script
    replace all docrnd with docshare
close databases

use branda
    go bottom
    store recno() to bra

use doccount
    go bottom
    store recno() to doc
close data

use base
    copy to input fields doctor,brand

use input
    append from lastb
    index on brand + doctor to inpbd

Clear

Select 1
Use input index inpbd
    store space(20)to brandx, doctorx
    store 0 to totcount,drugcount,s,ms
    store -1 to sum,brandcount

Do while .not. eof()
    if brand <> brandx .or. doctor <> doctorx
        ? brandx
        ?? space(1)
        ?? doctorx
        ?? space(1)
        ?? totcount

```

```

Select 2
  Use doccount
  locate for doctor=doctorx
  store doccount to wp
  if wp <> 0
    ?? space(1)
    ?? wp
    ?? space(1)
    store int(totcount/wp*100) to s
    ?? s
    store totcount/wp*100 to test
    if test>50

      Select 3
        Use brandcount
        locate for brand=brandx
        store roundms to ms
        ?? space(1)
        ?? ms
      endif
    endif
  endif

Select 4
  Use sumb
  append blank
  go bottom
  replace brand with brandx
  replace doct with doctorx
  replace xs with totcount
  replace dxs with wp
  replace sh with s
  replace b with ms

  Select 1
    store doctor to doctorx
    store 0 to totcount,ms
    if brand <> brandx
      store brand to brandx
      store 0 to drugcount
      store brandcount+1 to brandcount
    endif
  endif
  store totcount+1 to totcount
  store drugcount +1 to drugcount
  store sum+1 to sum
skip
enddo

set talk on
eject
close alternate
set alternate off
close data

```

```
use sumb
  go top
  delete for brand=space(18).or. brand=space(21)
  pack

use sumb1
  append from sumb
  set safety off

use branda
  go bottom
  store recno() to bra

use doccount
  go bottom
  store recno() to doc
close databases

sele 1
use sumb1
  replace all d_coun with 1
  go top
    do while .not. eof()
      store brand to brandx
      count to bra_tot while brand=brandx

sele 2
use sumb2
  append blank
  replace brand with brandx
  replace d_coun with bra_tot

sele 1
  enddo

set safety on
close data

sele 1
use sumb2
  go top
    do while .not. eof()
      store brand to brandx

sele 2
use sumb1
  sum xs,dxs for brand=brandx to xsa,dxsa

sele 1
  replace xs with xsa,dxs with dxsa
skip
enddo

close data

use doccount
  store reccount() to doc
```

```
use sumb2
  replace all b with d_coun/doc*100
  replace all w with x̄s/d_coun
  replace all wp with dx̄s/d_coun
  sum xs to total
  replace all ms with xs/total*100
```

```
set safety on
close data
```

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**Note:** References marked with an asterisk were used in the analysis in Section 1.6.

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